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ScienceDirect

Procedia Engineering 178 (2017) 67 – 75

Procedia Engineering

www.elsevier.com/locate/procedia

16th Conference on Reliability and Statistics in Transportation and Communication, RelStat'2016, 19-22 October, 2016, Riga, Latvia

BLUE Care: A Cooperative Location Network for Handicapped Persons

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Abstract

Many dependents such as children, elderly or disabled people get lost or missing, but as handicapped people, they often lack the skills to protect themselves, and tutors cannot keep their dependents in sight all of the time. Therefore, the challenge to be tackled in this paper is to develop a dependents' cooperative location network over which tutors could monitor the dependents' positions in real time, giving them more freedom to safely roam within public spaces. Not only in open spaces such as crowded parks or streets, but also inside buildings such as city malls, museums or nursing homes. The aim of this paper is twofold, to create a cooperative and dynamic network of tutors over which monitor the position of their dependents by means of standardized technologies, and to understand how the physical environment could influence handicapped people's activities by means of behavioral analysis in public spaces.

Peer-review under responsibility of the scientific committee of the International Conference on Reliability and Statistics in Transportation and Communication

Keywords: cooperative location networks, behavior analysis, mapping, safety, security, BLE-WiFi gateway, BLE motes

1. Introduction

Improving citizens' mobility in terms of their safety and security is one of the major concerns of cities all over the world. Half of the world population is concentrated in cities and by 2050 two thirds of world's people are expected

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Peer-review under responsibility of the scientific committee of the International Conference on Reliability and Statistics in Transportation and Communication
doi:10.1016/j.proeng.2017.01.064

to live in cities. This trend will increase the mobility challenge. Many citizens get lost or missing in cities, especially the children, our Nation's most precious resource, but as children, they often lack the skills to protect themselves. According to the Study on missing children from the European Commission by Cancedda *et al.*, (2013) in the European Union: on average, 400 out of every 100,000 children were reported missing within the period 2008–2012 in the European Union. Not only the children, but the elderly and disabled people (handicapped persons in general) are the focus of this work. Knowing the handicapped people's location is the key to knowing that they are safe by Steiniger, *et al.*, (2006). However, tutors cannot keep their handicapped people in their sights all of the time. Therefore, the challenge to be tackled in this work is to develop a cloud service over which tutors could monitor the handicapped people's positions in real time, giving them more freedom to safely roam within the public spaces and measuring their daily physical activity. Not only in open spaces such as crowded parks or streets, but also inside buildings such as city malls, museums or nursing homes.

Currently, the market offers four kinds of solutions for positioning the handicapped people. The first one uses a hose-clip or a wrist-band that integrates a GNSS (Global Navigation Satellite Service) receiver to determine the reallocation of the dependent, and a modem to send the geolocation data to the tutors via cellular networks. However, it has a high cost, around Euro 100, it needs an extra monthly fee due to the cellular data communication, and it does not work indoors. Some market offers can be founded in FiLIP (2016) and Tinitell (2016). The second one tracks the smartphone of the handicapped using their sensors. However, it can only be used for those that routinely carry a smartphone, uncommon for the handicapped's profile, and its availability indoors is limited. Some market offers can be founded in Situm (2016) and Proximus (2016). The third one uses a low-cost and battery free NFC (Near Field Communication) bracelet, such as the passive RFID (Radio Frequency Identification) technology, that is carried by the handicapped and whose position is updated every time their bracelet is detected by a NFC reader. However, its range is limited to a few centimeters which mean that a big amount of NFC readers would be needed to track the handicapped people. A market solution can be founded in Appkideak (2016). The last one is technology free and thus the cheapest one. It uses a bracelet where the main profile characteristics of the handicapped have been written down. However, it cannot track the handicapped and the bracelet has to be identified visually by Silincode (2016).

The proposed solution in this work uses a bracelet carried by the handicapped. The bracelet integrates a low-cost BLE (Bluetooth Low Energy) transceiver which regularly broadcasts a unique identifier (ID) at constant power. Its range depends on the transmission power and on the environment, but it usually ranges from 20 to 50 meters. The handicapped bracelet's position is determined within the range of a tutor/s BLE transceiver/s, while the positions of the tutors are assumed to be previously known – if the BLE devices are fixed (attached to a fix element) – or estimated by a location engine Bahillo *et al.*, (2016) – if the BLE devices are dynamic (attached to a moving element).

The target users who will benefit from this solution are the handicapped people living in a small, medium or large city where security and mobility issues are evident; and the tutors who will monitor for their safety. The customers will be the public administrations and nursing homes who looks for giving the handicapped people more freedom to safely roam within the public spaces, reducing the costs in security; the malls and commercial stores who look for improving their services' offer and advertisement; and the museums who look for knowing which area features are most visited and what not. The INTRAS Foundation INTRAS (1994) has been selected as one of the test location for the proposed solution. Its mission is highly concerned about the importance of guaranteeing safety and security for the handicapped people, enhancing the mobility of the handicapped in public spaces. INTRAS, which is the largest non-profit Foundation in the region of Castilla-León (Spain), showed its interest providing their facilities for testing the solution.

Section 2 introduces the localization engine which estimates the handicapped people's position. Section 3 describes the BLUE Care architecture and their main components, hardware and software. Section 4 discusses the BLUE Care potential. Finally, section 5 summarizes the main conclusions and future work.

2. The Seamless Localization Engine

Nowadays, the smartphones already integrate a GNSS receiver, a WiFi transceiver, a camera, and shortly, most of them will integrate other sensors such as the barometer and the proximity contactless technologies. The aim of the localization engine is to develop a framework that seamless estimates the user position by fusing the so called signals of opportunity (SoOP), signals which are transmitted for non-localization purposes, but may be exploited to this end. In fact, this engine is thought as a modular system for commercially available smartphones where SoOP coming from new technologies can be easily added.

Bayesian filters, which use a probabilistic framework to perform reasoning, 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 $t_k$by random variables x_k. At each point in time, a probability distribution over$\boldsymbol{x}_k$, 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 by Fox *et al.*, (2003). In this paper, the state is the user's location, $\boldsymbol{x}_k = [x_k, y_k, z_k]^T$, 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 user's location implies the usage of a suboptimal solution, where the most common is to use the EKF. Nevertheless, we selected the UKF since it better captures the higher order moments caused by the non-linear transformation and avoids the computation of Jacobian and Hessian matrices by Uhlmann *et al.*, (2000). Furthermore, the overall number of computations performed by the UKF is 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 of the smart devices.

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

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

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

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

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

where $\Delta t = t_k - t_{\{k-1\}}$ is the time step and $\dot{\boldsymbol{x}}_k$ is the first derivative of the state, in this case, the user's velocity. Finally, $\boldsymbol{w}_k$ is assumed to be a zero-mean Gaussian variable with covariance matrix $\boldsymbol{Q}_k$. The values of $\boldsymbol{Q}_k$ depend on the dynamic of the target, in this paper a walking person. In practice, $\boldsymbol{Q}_k$ is a diagonal matrix which in-diagonal elements represent the variance of the user's position and velocity by Wakim *et al.*, (2004).

On the other hand, the function $\boldsymbol{h}$ depends on the SoOP. In the WiFi or BLE case the measurement model, called $\boldsymbol{h}^w$, can be represented as

$$\boldsymbol{z}_k^w = \alpha - 10nlog_{10}(||\boldsymbol{x}_k - AP||) + \boldsymbol{v}^w{}_{\{k-1\}}, \quad (4)$$

where $\boldsymbol{z}_k^w$ 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 by Li (2006); AP is the position of the BLE -WiFi gateway; 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 by Pahlavan (2005). In this paper we dynamically estimate the path-loss exponent values following the algorithm proposed in Mazuelas *et al.*, (2009). By using this algorithm we found the path-loss exponents that best fit the propagation environment between the receiver (user's smart device) and each

BLE-WiFi gateway in range at each time interval. $\boldsymbol{v^w}_k$ represents the RSS noise and it can be assumed to be zero-mean Gaussian variable with covariance matrix $\boldsymbol{R^w}_k$. In practice, we have $\boldsymbol{h^w}_i$ with $i = 1,2, \dots, M_k$functions, where M_k is the number of BLE-WiFi gateways in range at each time step t_k. Accordingly, $\boldsymbol{R^w}_k$ is a diagonal matrix which in-diagonal elements represent the variance of the measurements coming from each BLW-WiFi gateway. The benefit of using this SoOP is thatBLE and WiFi signals predominate inside buildings where GNSS signals are blocked.

In the GNSS case, the measurement model, called $\boldsymbol{h^g}$, can be represented as

$$\boldsymbol{z}_k^g = \boldsymbol{x}_k + \boldsymbol{v^g}_{\{k-1\}}, \tag{5}$$

where $\boldsymbol{z}_k^g$ is the GNSS position estimation reported by the built-in GNSS receiver. $\boldsymbol{v^g}_k$ represents the GNSS noise which can be assumed to be zero-mean Gaussian variable with covariance matrix $\boldsymbol{R^g}_k$. In practice, $\boldsymbol{R^g}_k$ is a diagonal matrix which 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. We benefit from the GNSS data only in open areas where it accurately reports the user's position.

In the barometer case, the measurement model, called $\boldsymbol{h^b}$, can be represented as

$$\boldsymbol{z}_k^b = p_0 \left(1 - \frac{\gamma}{T_0} \boldsymbol{x}_k[3]\right)^{\frac{g}{\gamma R_{air}}} + \boldsymbol{v^b}_{\{k-1\}}, \tag{6}$$

where $\boldsymbol{z}_k^b$ is the air pressure, $T_0 = 288{,}15$ k is the temperature at sea level, $\gamma = -0.0065$ K/m is the temperature gradient, $p_0 = 1013.25$ mbar is the pressure at sea level, $R_{air} = 287\ \mathrm{m}^2(s^2K)^{-1}$ is the atmosphere gas constant, and $g = 9.8\ m/s^2$ is the earth gravity. $\boldsymbol{v^b}_k$represents the air pressure noise which can be assumed to be zero-mean Gaussian variable with covariance matrix $\boldsymbol{R^b}_k$. This model is not exact because it assumes some variables as constants, and it does not take into account other factors such as humidity, weather, or the presence of air conditioning systems. However, we do not use the absolute but the relative altitude. The estimated relative altitude is used to infer any building floor change.

Finally, in the contactless technologies cases using NFC tags or QR codes, the measurement model, called $\boldsymbol{h^c}$, can be represented as

$$\boldsymbol{z}_k^c = \boldsymbol{x}_k + \boldsymbol{v^c}_{\{k-1\}}, \tag{7}$$

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

As shown in Figure 1, and it is well described in Uhlmann *et al.*, (2000), 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) Uhlmann *et al.*, (2000).

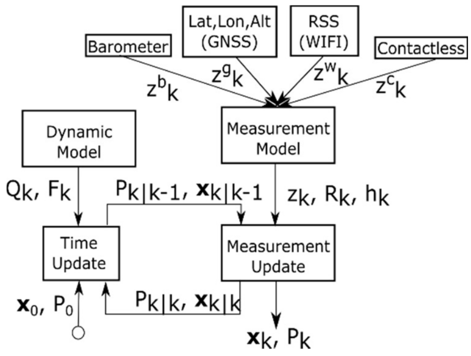


Fig. 1. Flowchart of the localization engine.

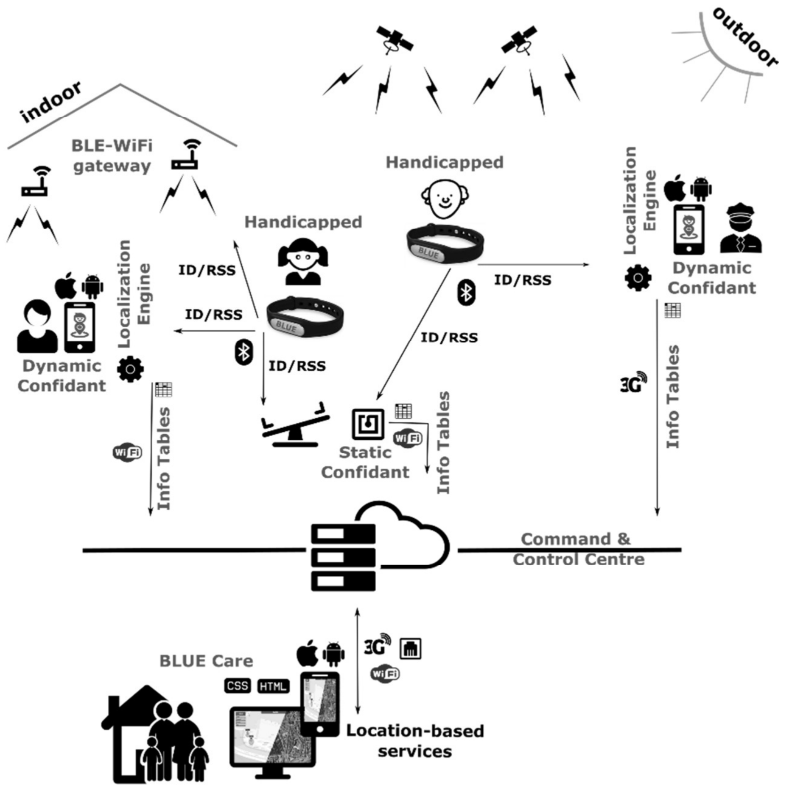
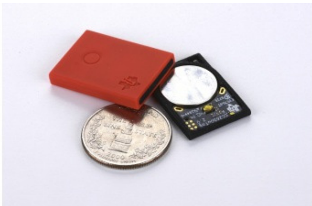


Fig. 2. Cooperative location network architecture. A back-end processing cloud service has been developed in order to provide a front-end consisting of a set of web services and a mobile application.

3. Cooperative Location Network Architecture

A back-end processing cloud service has been developed in order to provide a front-end consisted of a set of web services and a mobile application. The solution is based on a cooperative network of confidence devices. It defines two users' profile with unique identifiers (ID): confidant, assigned to the tutor, and handicapped assigned to the child, elderly or disabled. The confidence devices could be dynamic such as smart-phones, bands, watches or tablets; or fixed, deployed at strategic locations such as parks or streets in open spaces; and doors, stairs or rooms in indoor environments. The position of the fixed devices is assumed to be previously known, whereas the position of the dynamic devices is estimated by fusing the information gathered by its sensors (GNSS, BLE, WiFi, etc.) which were integrated for non-localization purposes, but that may be exploited to this end, for both indoor and outdoor public spaces. The confidence device integrates a Bayesian framework that considers both the sensors' information and the dynamics of the confidant. This way, the handicapped people's position will be estimated by processing the received signal strengths (RSS) gathered at the confidence devices in range of which positions have been previously estimated/known. Therefore, each confidence device will update periodically a table with its ID/position, and the ID/RSS of each bracelet in range. All the confidant tables are sent to the command and control center (in the cloud) where the position of the handicapped is computed using once again a Bayesian framework which in this case considers both the RSS and the dynamics of the handicapped. The higher the number of confidence devices, the larger the coverage of this network and therefore the higher the probability that a dependent will be accurately positioned.Figure2 represents the main components which describe the system architecture, and the flow chart of the data. These main components are the low-cost BLE bracelet, the BLE-WiFi gateway, the mobile application and the cloud which hosts the command and control center.

(a)



(b)

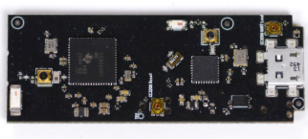


Fig. 3. The BLUE Care hardware-core: (a) the BLE bracelet; (b) the BLE-WiFi gateway.

3.1. The BLE Bracelet

The bracelet integrates a BLE transceiver aiming to broadcast the ID beacon which unambiguously identifies the dependent, the higher the transmission power the higher the coverage but the lower its battery life; an accelerometer aiming to measure the handicapped daily physical activity and to control the time interval between ID beacons, the higher the physical activity the lower the time interval; a vibration actuator aiming to warn the handicapped that something happens; and a clasp aiming to send a warning if the handicapped open the bracelet. Figure 3(a) shows the micro tag from Texas Instrument used as the core of the bracelet CC2650Microtag (2015).

3.2. The BLE-WiFi Gateway

A number of confidence fixed devices has to be deployed to guarantee minimum BLUE Care coverage because it depends on the network of confident devices, and the dynamic confident devices such as smartphones depend on the number of enrolled tutors. Figure2 shows the BLE-WiFi gateway from Texas Instrument used as the core of our BLE-WiFi gateway by Bluetooth Smart to Wi-Fi IoT Gateway (2015).It integrates two wireless interfaces: BLE and WiFi. The BLE acts as the interface between the handicapped (the BLE bracelet) and the tutor (in this case a fixed mote), while the WiFi acts as the interface between the tutor (in this case a fixed mote) and the command and control centre hosted in the cloud. Both interfaces share a buffer to interchange the data. The BLE interface fills the buffer with the selected BLE IDs and its corresponding RSS belonging to the enrolled bracelets. The WiFi interface empties the buffer whenever the IDs/RSS info is sent to the command and control centre. The BLE-WiFi gateway could be powered by a battery supply or directly to the mains power depending on the environment. Likewise, the command and control centre could send messages to the BLE-WiFi gateway aiming to restart them update their firmware, change their state between idle and wake-up, etc.

3.3. The Mobile Application

The core of the mobile application is the localization engine which performs seamless localization estimation of the tutor's device in real time by fusing the information collected by all of its sensors. Nowadays, the smart devices such as smartphones, smart watches or tablets already integrate a GNSS receiver, a WiFi and Bluetooth adapters, a camera, and shortly, most of them will soon integrate other sensors such as the barometer, inertial sensors or the proximity contactless technologies. Therefore, taking into account this sensors' information and the dynamics of the tutor, a Bayesian framework is used to estimate the position of the tutor by Bahillo *et al.*, (2016). Once the tutor's position is estimated, several functionalities based on the context would be implemented. Therefore, the localization engine would be the ideal platform for developing location-based services that provide the tutor with context-based information Steiniger *et al.*, (2006). Among these services, the mobile application mainly allows the confidant looking up the location of his/her handicapped, knowing if they go out of the tutors' range, editing alarms in order to better control his/her handicapped, and pressing the panic button in case of an emergency, i.e. a missing handicapped. If this would be the case, the confidant profile could notify the system asking the enrolled users for enabling his/her confidence devices. Thus, the area of coverage will be enlarged.

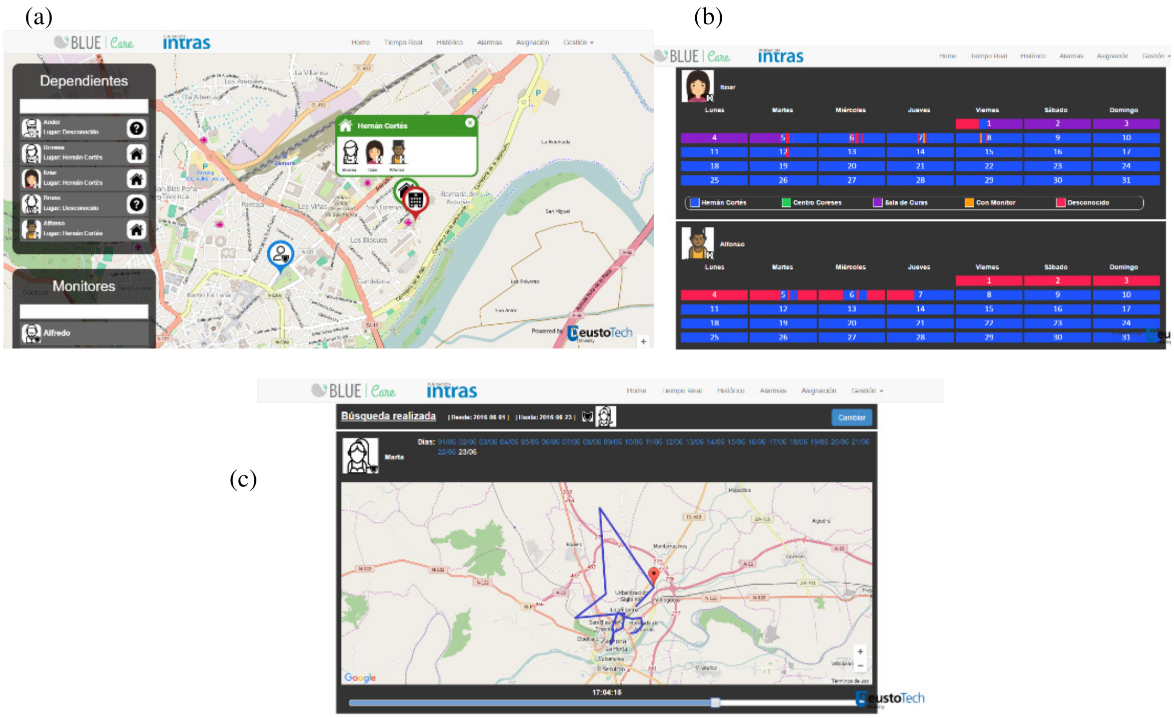


Fig. 4. The command and control center: (a) real time; (b) handicapped past positions (room accuracy); and (c) tutor's past positions (GNSS accuracy).

3.4. The Command and Control Center

The aims of the command and control center are to remotely track the position of all the tutors and handicapped people, edit alarms, control the fixed BLE-WiFi gateways, monitor the handicapped physical activity, and analyse the behaviour of the users. As explained earlier, the position of each handicapped is computed in the command and control centre, so each confidence device will send periodically a table with its ID/position, and the ID/RSS of each BLE bracelet in range. A localization engine is used to estimate the position of each dependent considering both the

RSS and the dynamics of the handicapped. Furthermore, this command and control centre could provide the services based on the context, such as offers, advertisement, advice, etc. Figure 4 shows a general view of the command and control centre.

4. Discussion

Beside the main goals of such tools providing safety and supporting comfort of people using various places, such tool can provide information for spatial-behaviour analysis to inform better practice in design, maintenance as well as surveillance of places. This paper foresees the implementation of behaviour mapping-related methods to provide a variety of information about dependent-tutor-spatial relationships. Such relationships will be examined on an individual basis, studying each single situation, analysing distances and characteristics of places between tutor and dependent to address ease of way finding between them, as well as legibility of sequences of places they are involved with. Studying all dependent-tutor behaviour patterns in the given area, the paper will address cumulative carrying capacity of place for ease to navigate through the place and search for spatial clues, where it is more likely that people could get lost or confused, and how these clues could be similar for different users; different types of handicapped and their tutors. Thus, it is assumed that the implementation of the cooperative location network discussed in this paper can significantly improve information and knowledge about (vulnerable) users in their environments and help to create inclusive design guidelines or recommendations for safe and easy-to-navigate places.

Having gathered behavioural information in time and space, several types of analysis are possible: from straight forward and descriptive in nature such as: *How many people access the public space averagely every day?*; to more space oriented, such as: *Which is the area that is most utilized utilised during weekends?*, or *Which area features tend to foster exploratory play in children?*. In this respect the aim of this paper is to provide socially informed concepts and measures for public spaces and to show a potential which ICT driven tools can have for recording and evaluating behaviour patterns and their characteristics; not only to provide safety measures but to address thresholds and evidence-based guidance for urban planning, design and architecture in order to work towards quality of living in cities and towns.

5. Conclusions

The cooperative location network that has been presented in this paper shows a new service over which tutors could monitor their handicapped positions in real time, giving them more freedom to safely roam within the public spaces. Besides the main goals of such digital tool providing safety and supporting comfort of people using various places, such tool can provide information for spatial-behaviour analysis. Behaviour maps provide a shorthand description of the distribution of behaviours throughout a place. They are useful if sufficient repeated observation in a place is done. The major value of behaviour maps as a research tool, lies in the possibility of developing general principles regarding the use of space that apply in a variety of settings. Overlapping individual behaviour maps can show some characteristics and changes in using spaces in terms of activities, number of people engaged, gender, and all the other variables that are explored. Focusing on safety and comfort in places, they can also help to provide empirical knowledge about way finding and vulnerable users' difficulties in specific user-place or user-user situation in the observed setting. Thus, there is a challenge to set up and promote a monitoring digital tool which can as much as possible unobtrusively function for users' engagement with places as well as the device/tool itself.

Acknowledgements

This work has been supported by the Spanish Ministry of Economy and Competitiveness under the ESPHIA project (Ref. TIN2014-56042-JIN).

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