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Identification and distance estimation of users and objects by means of electronic beacons in social robotics

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Abstract

Social robots are intended to coexist and to communicate with humans in a natural way. This requires these robots to be able to identify people (and objects) around them to use that information during human-robot dialogs. In this work we present how electronic beacons can benefit the interactions between humans and social robots. In particular, Bluetooth 4.0 Low Energy beacons are presented as the most suitable option, among the up-to-date available technologies. In order to show the advantages of the system during human-robot interaction, first, we present the integration of the information provided by these devices in the robot's dialog system; and after, a *hidden toy hunt* game is described as a case study of a scenario where electronic beacons ease the interaction between humans and a social robot.

Key words: Electronic beacons; Social Robots; Human-Robot Interaction; Bluetooth Low Energy; User identification; Object identification

1 Introduction

Social robotics is a research field where natural interaction between humans and robots is essential. In order to achieve this kind of interaction, it is necessary that robots identify the people involved in the interaction. Moreover,

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the identification of the different objects in the environment also improves the interaction capabilities of the robot while communicating with people. This ability, people and object identification, would improve the social capabilities of a robot by, for example, making it more friendly (for example calling people by their names) or enriching the robot's communication (for instance being able to answer questions about nearby objects).

Equally important is their capacity to localize people. In social robotics, the interaction can be adapted depending on the distance between the robot and the user. Moreover, personal localization is crucial to adapt the interaction to the personal spatial zones. In 1966, Hall investigated in proxemics (physical and psychological distancing from others) and identified four personal spatial zones that are important during interpersonal relations (Hall, 1966). Later, Walters et al. studied how these zones during human-robot interaction varied depending on the human's personality traits (Walters et al., 2005) and analyzed the most comfortable distance for HRI. Therefore, distance estimation is a crucial feature that helps robots to conduct more natural human-robot interaction (HRI).

In general terms, the technologies used in social robotics for user and object identification and distance estimation are inspired in the way humans perform these same processes, that is, through vision or hearing. However, to date, these technologies are not accurate enough and in many cases they present some difficulties: for example, if there is not a direct line of sight between the robot and the object to be recognized, computer vision techniques cannot be applied; in the case of audio-based techniques, if the user does not talk or if she is far from the robot, the robot will not be able to locate (or identify) the person.

In order to overcome these limitations we propose to use Electronic Beacons (EBs). An EB is a device, normally about the size of a coin, that emits a specific wireless signal periodically. The emitted signal can be received by any compatible receiver placed inside the influence area of the advertiser (or emitter [1]). The potential of EBs is not in the device itself but in software that understands and attends the signals emitted by the beacon (Newman, 2014). Therefore, we do not focus on the development or improvement of a particular technology, but on the application of EBs to the area of Social Robotics and how they can be used during HRI.

EBs have been extensively applied to many fields such as advertising (Deordica & Alexandru, 2014), electronic payment (Jeffus et al., 2015), or leisure activities (Rontidis et al., 2015; Smith, 2015). In robotics, EBs have been applied to robot localization (Navarro-Serment, 1999; Cuadra-Troncoso, 2015), or object

[1] The terms beacon, emitter, advertiser, and transmitter, are indistinctly used along this paper because all of them refer to a device that emits a signal periodically.

localization (Schwarz et al., 2015). However, to the best of our knowledge, its application in social robotics has not been presented yet. In this paper, we introduce and justify the use of EBs in social robots for identification and distance estimation of humans and objects[2] in order to improve the robot's communication capabilities. We propose to apply EBs to HRI scenarios and integrate this technology into a dialog management system to improve the communication between the robot and people. In this work, we aim at showing the advantages of using the information provided by EBs to identify and localize people and objects around a social robot while interacting[3].

The rest of the paper is structured as follows. In Section 2, we describe the methods traditionally used in robotics to identify and localize objects and users and comment their inconveniences. Following, in Section 3, we present the main technologies in which EBs can be based. Here, we analyze different features and summarize the pros and cons of the technologies (Section 3.1); besides, in Section 3.2, we justify the selection of Bluetooth 4.0 Low Energy (BLE) beacons. Then, Section 4.1 describe how to perform a reliable distance estimation using BLE beacons and a robot. Later, Section 5 illustrates the benefits of EBs in social robotics using two examples: a robot dialog system that uses the information provided by EBs (Section 5.1), and a study case where, by means of EBs, children play an interactive *hidden toy hunt* game with a robot (Section 5.2). Finally, the conclusions of this work are commented in Section 6.

2 Object and user identification in robotics

As mentioned earlier, one important feature of many robots is their ability to interact with objects in the environment. In a prior step to this interaction, robots need to identify and localize the objects they are intended to interact with. Following the same means humans use, researchers have traditionally used two types of information for these purposes: visual and audio data.

Currently, there are several works focused on the identification and localization of users and objects placed around the robot based on computer vision. Dondrup et al. (Dondrup et al., 2015) used an RGB-D camera and a laser to detect and track humans in the vicinity of the robot while it performs human-

[2] People identification can be considered as a particular case of object identification. We make the distinction between objects and people to strengthen the relevant role of people while interacting with social robots

[3] **It is important to mention that orientation estimation is out of the scope of this paper and will not be considered as a requirement along this paper**

aware navigation. In the RoboEarth project (Di Marco et al., 2012; Mohanarajah et al., 2015), objects were identified using vision techniques based on 3D cameras and processed in the cloud. In addition, recently Bogun (Bogun et al., 2015) recognized objects using a 2D camera and applying automatic learning algorithms based on Deep Learning. Authors obtained a high rate of success (up to 82%) using the Washington Scenes Dataset. An equivalent system using the object recognition system developed by Google obtained 83% of success in object identification (Kehoe et al., 2013). In general, these vision techniques require complex algorithms, calibration processes and the use of expensive cameras. Moreover, the performance is affected by variable light conditions and require a direct line of sight between the items and the cameras. The main strength of vision-based techniques is that they do not need any environmental modification.

Recently, Castillo et al. proposed an architecture for robust people detection through fusion of infrared and visible image sources (Castillo et al., 2016). Their system performs human detection in the infrared spectra using a threshold-based approach, and in motion history for the detection in the visible spectra. Correa et al.presented an approach for people identification using visual and thermal cameras in domestic environments (Correa et al., 2011). Combining data from the visual and thermal spectrum, they applied several algorithms, such as, face detection, skin detection, and human pose detection. The results showed that the identification accuracy is affected by the interaction distance, the light conditions, and the user pose (the user must be facing the robot). Another approach, compared the accuracy of optical flow and image subtraction techniques for human detection from infrared cameras mounted on a mobile robot (Fernández-Caballero et al., 2010).

Using auditory data, a robot does not require a direct line of sight to identify a person but it cannot be used for object identification. Besides, the performance decreases significantly when the robot is in a noisy environment. The echoes of the voice signals due to the walls and other objects affect its reliability. Alonso et al. perceived humans' utterances and analyzed them using signal processing algorithms to localize and identify users interacting with a robot (Alonso-Martin et al., 2014; Alonso-Martín et al., 2012). For the identification process, a successful rate of about 70% is obtained, considering up to eight different users speaking at different times. Other project related to human identification and localization using the audio channel is the HARK project (Nakadai & Takahashi, 2010). Nakadai et al. claimed that this system was able to recognize up to three simultaneous speakers with a word correct rate between 80% and 90%.

Apart from image and audio analysis there are other techniques for object and human localization and identification that use beacon-like technologies. Schwarz et al. used EBs to roughly localize static objects around a robot for a grasping task, in combination with other sensors (Schwarz et al., 2015). Small beacons were attached to each object and, at least four receivers were placed in known positions surrounding the robot. The system took between 10 and 30 seconds to estimate the approximate position of each advertiser with an error between 20% and 50%. This long processing time makes impossible to apply it to HRI scenarios. In social robotics, Corrales et al. introduced radio frequency identification (RFID) technology for object identification (Corrales et al., 2008); the social robot Maggie was able to identify drugs that had an RFID tag inside their boxes and inform about the medicine name, its date of expiration, and when it had to be taken. In this work, the medicine box had to be in contact with the robot's head (where the RFID reader was located) to provide a reliable identification. This was not intuitive for many users and not very natural in terms of HRI.

The different techniques presented in this section have several drawbacks that can be overcome using electronic beacons with a proper configuration. EBs are very robust to variations in the ambient conditions, such as the light condition, noise, or obstacles that can block the robot's line-of-sight. Besides, EBs are very ease to install and can be attached to objects the robot needs to detect. Actually, many smartphones already include EB technologies and can be used as a non-intrusive people detection device. In addition, their wide working range (see Section 3 for more details) eases a natural interaction.

3 Electronic beacons and the underlying technologies

As just mentioned, EBs represent a promising solution to the current limitations of object identification and distance estimation in robotics. EBs are small, light, electronic devices that emit a signal periodically. The emitter transmits a signal containing usually a unique identification code and, some times, other data. A receiver reads the signal emitted by the beacon and make it available for processing. EBs can be based on different wireless communication technologies (e.g. radio frequency or visible light communication) underpinning different communication protocols. In this section we analyze the available technologies and compare them to select the most suitable one for social robotics.

3.1 Relevant technologies

The current expansion of EBs began with the development of the **Bluetooth 4.0 Low Energy (BLE)** technology. A BLE beacon has a reduced size (approximately $2cm * 2cm$), its cost is generally low (from \$5 to \$20), and it has a high battery duration (up to 2 years depending on the manufacturer and the configuration of the beacon). There are different companies that have developed their own BLE beacon technologies. The most popular one is the *iBeacons* developed by *Apple Inc.* in 2013 (Dilger, 2013). An *iBeacon* can be configured to operate in an influence area of 70 meters in any direction. The iBeacons have been used many times for localization tasks. According to Newman's studies in indoor localization, it is possible to obtain an accuracy of 0.53 m using multiple advertisers (Newman, 2014). In the same line, Cho et al. claimed that iBeacons only allows us to obtain a faint estimation of the distance: very close (less than 0.5 meters), close (from 0.5 to 2 meters), and far (from 2 to 70 meters) (Cho et al., 2015). They obtained an average error of 46.3% in distances between 0.4m and 1.4m. In order to improve the accuracy in the estimation of the distance, Cho et al. proposed adding an extra advertiser located exactly at 1m from the receiver. Using this additional iBeacon he reduced the average errors to 4.7% for distances between 0.4 and 1.4m. This method can only be applied in cases where the receiver has a fixed position in order to maintain the 1 meter distance with the extra advertiser.

There are other studies focused on iBeacons applied to smartphones, like the one proposed by Alam et al. (2015). Here Alam et al. claimed that the measurements of the errors are not linear, but they are proportional to the physical distance between the advertiser and the receiver. The average error within a 1 meter range is negligible, but it increases up to 2 meters in a 10 meter range (20% of error). The accuracy of BLE beacons was extensively studied by Faragher & Harle (2014). This study stated that the human body is an obstacle that produces an attenuation of the BLE signal. Besides, due to its small bandwidth, the intensity of the BLE signal fluctuates and it is prone to interferences caused by a Wi-Fi signal. In this line, Silva concluded that a part of the BLE signal is absorbed by the human body, while conventional Bluetooth, X-Bee, or Wi-Fi do not seem to affect BLE signal (Silva et al., 2014).

Other company, *Quuppa*[4], has developed its own BLE beacons to localize and track objects that are moving at high speeds, both indoors and outdoors. This technology allows, in addition to calculating the distance between an advertiser and a receiver, to know the exact position of the device within 0.1 meter error. This technology differs from other methods that use BLE in the position and distance calculation: the method used is not based on the power of the signal (RSSI), but on the arrival angle of the signal (P & Sichitiu, 2006). *Quuppa* uses a device formed by several antennas located at fixed distances from each other as the receiver.

[4] Quuppa website: http://quuppa.com/

In the recent years, *Google Inc.* also has developed its own EB system, known as *Eddystone* [5], based on BLE beacons. Its applications are similar to those of iBeacon and in many cases are compatible. In this same line, the *AltBeacon* project[6] presented an open protocol that defines the messages broadcast by BLE beacons. To date, there are just few applications using this open protocol.

Radio Frequency IDentification (Roberts, 2006) is a technology for automatic identification and data capture. Its main goal is to transmit the identity of an object (with a unique serial number) through electromagnetic waves. An RFID system is composed of RFID tags attached to the objects to identify, and a reader. These beacons refer to active RFID tags which have their own source of energy to transmit the signal. Notice that passive tags are not considered as beacons because they do not continually emit periodical signals, but they use the energy of the signal provided by the antenna of the RFID reader to emit. RFID beacons have a range of operation between 10 centimeters and 100 meters, depending on the kind of tag and the antenna of the receiver. The size of the antenna is proportional to the range of operation. Their battery can last more than a year and their price is about several tens of dollars. This technology has been used in robotics for indoor localization (Deyle et al., 2010; Boccadoro et al., 2010; Kulyukin & Gharpure, 2004). In these works, using low range RFID tags,robots updated is localization in the map when detected a RFID tag (each RFID tag was associated to a certain place).

Near Field Communication (NFC) (Want, 2011) is a wireless technology derived from RFID that operates in high frequencies and low distances. The communication between two NFC devices requires two NFC antennas (one installed in each device) placed inside their respective action ranges for a direct communication. NFC is a high speed communication system with a reduced action range (maximum of 20 cm) that limits its applications. One of its main applications is people identification for access control where users need to bring their NFC chip close to the reader device (Ok & Coskun, 2010). Other widespread application is mobile payment service (Jeffus et al., 2015).

Other technology for EBs is **ZigBee**, a set of high level protocols for wireless communication using digital low energy broadcasting (Alliance, 2009). This technology is focused on applications that demand secure communication with low data rate and low energy consumption. ZigBee is one of the most efficient technologies in energy consumption used in wireless communication. ZigBee-based approaches provide network load balance to extend network lifetime, efficiency improvements, and data loss avoidance (Ortiz et al., 2013). ZigBee allows the creation of complex local area networks where multiple devices are interconnected. Thus, ZigBee is used to cover wide areas (e.g. a whole

[5] Eddystone website: `https://developers.google.com/beacons/`
[6] AltBeacon website: `http://altbeacon.org/`

house), in contrast to other technologies, such as BLE, that are intended for small areas (Technologies, 2016). The first time a device is used in a ZigBee networks, it has to be paired manually.

Ming-Hui et al. used ZigBee to develop an indoor tracking system of people for smart homes (Jin et al., 2007). In this system, several ZigBee beacons were placed in known positions and the users carried a ZigBee receiver that, based on the energy of the signal received from the beacons, determined the position of the user in the environment. Olivares et al. developed a ZigBee-based system for data gathering in intelligent buildings, monitoring environmental indoor conditions, such as temperature and humidity in an office space (Olivares et al., 2007).

In robotics, ZigBee is highly extended. One of its first applications is the wireless teleoperation of robots (Min Huasong et al., 2010). Moreover, Wang and Yu used ZigBee beacons as marks in the environment for robot navigation tasks (Wang et al., 2010). In the case of Rashid et al.'s work, a *host* robot moving in an aquatic environment sends information to a *master* robot through ZigBee technology (Rashid et al., 2012). Chia-How et al. developed a security system where a ZigBee network of sensors detected intruders and communicated with a robot that moved to the intruder's location and took images of them (Chia-How Lin et al., 2008).

EBs can be based on **Z-Wave** too, a wireless communication protocol designed to provide a reliable, low latency transmission (Alliance, 2015). It was intended for home automation, interconnecting all devices of an intelligent house. In ideal conditions, this technology has a maximum operational range of 40 meters.

Z-Wave technology uses two types of devices: (i) the controllers, that keep track of the devices connected to the network and are responsible for managing the network; and (ii) hosts, that are commanded by the controllers and ignore the network structure. Before a device is used in a Z-Wave network, it has to be paired manually.

In relation to its applications, Z-Wave technology has also been used in robotics. In particular, the social robot *AISoy* uses this technology to control all the devices in an automatic home network (García et al., 2011).

In contrast to the previous radio-based technologies, **Light Fidelity (Li-Fi)** technology is a wireless communication system that uses visual light. This is a fast, free of electromagnetic interference, high security technology (Medina & Navarro, 2015). The communication between the advertiser and the receiver is performed thanks to ultra fast visible light variations that modulate a pulse signal. A drawback of this technology is that it requires a direct line-of-sight between the advertiser and receiver with an action range up to 10

Table 1
Technical details of the technologies which can be used as electronic beacons. *Release Year*: year that the first version of the technology appeared. *Freq.*: operating frequency; in case of multiple frequencies are possible, the lowest and the highest ones are presented. *Battery*: maximum duration of the battery of the advertiser. *Max.range*: maximum theoretical operating distance. *Maximum bit rate*: maximum theoretical bit rate. *Transmitter price* and *Receiver price*: range of prices for an emitter and a receiver obtained from several specialized websites.

Technology	Release Year	Freq.	Battery duration	Max. range	Maximum bit rate	Transmitter price ($) $[min - max]$	Reciever price ($) $[min - max]$
BLE	2010	2.4 Ghz	2 years	70 m	1Mbps	1-20	10-25
Active RFID	1983	100Khz 2.45GHz	5 years	100 m	1Mbps	1-5	100-600
ZigBee	2003	2.4 Ghz	12 years	290 m	250 kbps	5-25	5-25
Li-Fi	2011	430THz 770THz	Unknown	10 m	224 Gbps	Unknwon	Unknown
ZWave	2005	908.42Mhz	1.5 years	100 m	40kbps	55-65	55-65

meters. Currently, this technology is at the early stages of development and it is not very extended. However, it has already been used for indoor localization (Ganick & Ryan, 2012).

3.2 Selecting a technology

Among the characteristics defining the above described technologies, it is important taking into account the common features that are specifically important for the application of EBs in social robotics. First, all of them have to provide wireless communication. Despite it ought to be obvious, wireless communication is a must since, in daily environments, people come and go at their will and objects can be moved freely. Second, the energy consumption of the devices needs to be low in order to foster the acceptance of EBs by people. Looking into Table 1, we see that the battery duration of all the studied technologies present devices that last for years (except for Li-Fi which is in an experimental phase and data is not available). Finally, due to the nature of EBs, all technologies provide a reliable identification when the beacon is inside the operation range of the receiver.

Analyzing Table 1 and keeping in mind that our goal is the application of EBs to social interactions, all technologies, except for Li-Fi, provide a wide operation range. Even though Li-Fi is robust to electromagnetic interferences (it uses visible light instead of radio signals to communicate), Li-Fi is the only one that requires direct line of sight between the emitter and the receiver.

Table 2
Comparison of the main requirements for the application of EBs in social robots. Drawbacks are highlighted.

Technology	Operation range	Degree of maturity	Pairing required?	Direct line of sight required?	Cost of the technical devices	Prone to electromagnetic interferences?	Size of the devices
BLE	wide	high	no	no	low	**yes**	small
Active RFID	wide	high	no	no	**high**	**yes**	**big**
ZigBee	wide	high	**yes**	no	low	**yes**	small
Li-Fi	**short**	**low**	**yes**	**yes**	**high**	no	small
Z-Wave	wide	high	**yes**	no	low	**yes**	small

These limitations represents an important drawback and therefore we consider that Li-Fi beacons are unsuitable for social robotics.

Technologies that need *pairing* (in our study ZigBee and Z-Wave) require manual "registration" of all beacons before they exchange information. This limits the flexibility and usability of the system and consequently they will be avoided.

In the last two columns of Table 1 we find the range of prices of emitters and receivers. As the reader can see, the prices are relatively low particularly for the emitters. Just in the case of the active RFID receiver the price may rise up to $600. Moreover, as already stated, in case we desire a considerable operation range, the size of the RFID antenna increases considerably and it can represent a problem when it has to be embarked in a robotic platform with limited space.

In order to summarize all the pros and cons of the described technologies, and considering the technical details included in Table 1, Table 2 presents an easy-to-read summary of the most relevant features to be considered for the application of EB to social robots. In light of the foregoing features and considering the requirements of our system, we believe that BLE is the most suitable technology for object identification and distance estimation in social robots. Although BLE is a technology that can be affected by interferences due to many reasons, we believe that we can deal with interferences if we conduct a thorough calibration considering the particularities of our system. The following section tackles this crucial aspect in BLE in order to address its performance in different meaningful situations for HRI.

4 Distance estimation using BLE

The literature contains several methods to estimate the distance between an advertiser and a receiver. These methods differ on the magnitude they measure:

(1) Arrival time. The distance is calculated based on the time that the emitted signal takes to get from the advertiser to the receiver. Two synchronized clocks are needed.
(2) Arrival angle. Several receivers, placed in known positions, are used to measure the angle formed with the emitted signal and the distance is computed by triangulation.
(3) Arrival energy. Based on the energy of the signal detected at the receiver, the distance can be calculated considering the attenuation of the signal.

The first method, based on the arrival time, was discarded since it requires two expensive, accurate clocks. The second method, based on the arrival angle, was also discarded because of the high cost of the array of antennas required in the receivers. Besides, considering the limited space inside a robotic platform, the size of this array represents a restriction. Consequently, the third method based on the attenuation of the energy of the signal has been selected. The reason is twofold: (i) it is cost-efficient, and (ii) it does not require a special environment configuration. The main drawback of this method is that the system must be calibrated previously. It is important to mention that the calibration process is a mandatory step for distance estimation, but not for object identification. This means that, when distance estimation is not relevant, object identification can be conducted without calibration.

Seybold presented an equation to measure the distance to an advertiser based on the energy of the emitted signal detected by the receiver, Equation 1 (Seybold, 2005). This method depends on the attenuation of the signal which in turn depends on the BLE devices and the interferences.

$$d = A * (RSSI/txPower)^B + C \tag{1}$$

d is the distance (in meters), $RSSI$ is the energy of the received signal (dBm), and $txPower$ is the energy of the received signal when the advertiser is placed exactly at one meter far from the receiver (dBm). This parameter can be calculated empirically or supplied by the manufacturer. A, B, and C are the coefficients that will be obtained after the calibration process. In order to get these coefficients, we measure the signal energy ($RSSI$) keeping the beacon at multiple predefined distances (e.g. d equal to 1m, 2m, 4m,...). To improve the accuracy and robustness of the system, it is necessary to obtain multiple measurements of the received energy from the same distance in order to take an average of the *RSSI* value for that distance. Once we have the averaged RSSI values for the set of predefined distances, we conduct a linear regression to define A, B, and C. These coefficients, together with Equation 1 and the detected signal energy, will be used to determine the distance d between a BLE beacon and a receiver on real time.

4.1 Calibrating the BLE system for our robotic system

Calibrating is a sensitive process that depends on several parameters, such as the specific advertiser-receiver or the electromagnetic interferences. Consequently, in order to be able to estimate the distances properly, we need to calibrate our BLE system for our particular settings.

In this work, we propose that BLE beacons are carried by users or attached to several items, and the receiver is connected to a social robot. A USB, BLE receiver dongle was connected to a computer running an Ubuntu OS and located inside the robot's body. Specifically, we used a Plugable Technologies USB-BT4LE device[7]. The advertisers (BLE beacons) used in this work are manufactured by DFRobotics[8]. Each beacon has been configured with a specific identifier and device name. In order to adjust the identifier, the power of the emission, and the frequency of each advertiser, we used the free application *LightBeacons* for iOS. In particular, the emitting frequency is a key parameter that impacts directly on the battery life. If the emitting frequency is high, the advertiser will deplete its battery in a short time. Using this tool, we set up the emitting frequency of the beacons to 2 signals per second with which, according to the data sheet, the beacons battery should last around up 2 years. Figure 1 shows both the receiver and an advertiser. These devices were selected because of their low price and Ubuntu compatibility. However, any BLE beacon could be used in our system.

Fig. 1. The BLE advertiser (right), receiver (left), and a power cell CR2450, that is inside the advertiser (center). The pen is shown to compare the sizes.

[7] Guide to select a bluetooth adapter: https://goo.gl/ZMK083
[8] https://goo.gl/lJce7J

In order to get the A, B, and C coefficients for Equation 1, first it was necessary to obtain the *txPower* parameter. We placed the robot in a predefined position and located a BLE beacon at 1 meter. Then, we measured the *RSSI* value for that configuration. After that, we repeated the process placing the BLE beacon in fifteen different distances (ranging between 0.25 and 17 meters), acquiring a total of 150 measurements of the arrival energy from each configuration, and computing the average value for each distance. **Once we had the averaged values for all distances, we performed a nonlinear regression. According to the R^2 value, the regression accounted for $91,6657\%$ of the variability of distance and the *Adjusted* R^2 value was $90,1503\%$. Seeing that the residual were approximately uniformly distribute and the R^2 and *Adjusted* R^2 values were close to 1.0, we could confirm that our regression model is a good fit of the data. The obtained values for our parameters are presented in Table 3.**

Table 3
Obtained values of the parameters needed for distance estimation after the calibration process

Parameter	**Value**
txPower (dBm)	−66.52
A	−380
B	5.47
C	−3.80

4.2 Improving the distance estimation

Once the coefficients and the *txPower* are obtained, we can estimate the distance to a beacon. In order to reduce the effect of possible interferences or the fluctuation of the received signal energy, we read the energy signal of a beacon several times to average its value before we calculate its distance d. It is expected that increasing the number of readings will improve the accuracy of the estimation. Nevertheless, each reading requires a certain time, therefore, it would happen that the total time required for a high number of readings will cause a delay too high. Besides, once we have defined the number of readings, we need to define how to average the arrival energy. In this work, three possibilities have been considered: the mean value, the median value, and the mode value.

In order to determine the number of readings and how to average the arrival energy, we conducted a test where to compute the distance estimation error using different configurations. The results are summarized in Table 4. We placed the beacon at 0.1, 2, 4, 8, 11, and 14 meters away from the robot and read the signal energy detected. We computed the mean, the median, and the mode of windows of 3, 5, 9, and 37 readings. As shown in Table 4, 1 reading implies a high error in short distances (0.1, 2 and 4 meters). In general, making 5, 9, or 11 readings improves the accuracy of the estimations. However, making those readings will cause a bigger delay in the distance estimation and consequently in the robot response. Considering the final application (HRI applications), a high number of readings implies a big latency (considering that we configured advertisers to emit every 0.5 seconds) that will make the system impossible to be applied in HRI. The decision about the number of readings implies a trade-off between the latency of the system and the accuracy of the measurements.

In view of the study conducted by Shiwa et al. (Shiwa et al., 2009) where authors stated that the response time of communicative robots should be kept between one and two seconds, we have decided to use a 3-reading window, i.e. $1.5s$ delay, to estimate the distance to a beacon. A bigger time delay during HRI may affect the interaction negatively. Therefore, making 3 readings represents our compromise to get an accurate enough estimation with a suitable time delay.

In relation to the method to average the arrival energy, according to the results, the mean value provides the best estimation (except for the beacon at 4 meter). Concerning the mode, it could happen that several values are repeated the same number of times and then we do not obtain a unique mode value (this is the case when we consider 3 readings of a beacon located at 11 meters in Table 4). We decided to use the mean value.

Notice that, considering a 3-reading window and its mean value, the relative distance estimation error when the beacon is very close ($0.1m$) is very high (110%). This makes sense because at very short distances, a small error implies a high relative error. Excluding this case, the average relative error for all distances is 14.88% .The mean raw values and the relative errors for the 3-reading window configuration have been highlighted in Table 4. This can be seen as the empirical data of the accuracy of the distance estimation.

According to these results, our method and **heuristics** outperforms some of the existing methods in the literature (e.g. (Schwarz et al., 2015)). Although this technique does not give a highly accurate distance, we believe that it can be applied to HRI scenarios where the distance estimation of objects and people do not need a high accuracy, and can be related to delimited zones. Let us imagine a robot trying to attract the attention of a person. In this situation the robot could say something like *"Hi! I want to talk to you but you are too far so I cannot understand you properly"*; however, the interaction with the robot would be perceived as unnatural if it communicates using sentences as

Table 4
Distance estimation locating a BLE advertiser at different distances and considering 1, 3, 5, 9, and 37 readings for each configuration. We have estimated the distance using the mean, the median, and the mode values. Empirical data for the selected configuration (mean value for 3 readings) has been highlighted.

Real distance	Number of readings	Mean		Median		Mode	
		raw	Rel.err.	raw	Rel.err.	raw	Rel.err.
0.1m	1	0.94m	840%	0.94m	840%	0.94m	840%
	3	0.21m	110%	0.93m	830%	0.93m	830%
	5	0.28m	180%	0.93m	830%	0.93m	830%
	9	0.10m	0%	0.10m	0%	0.93m	830%
	37	0.18m	80%	0.10m	0%	0.93m	830%
2m	1	1.74m	13%	1.74m	13%	1.74m	13%
	3	1.89m	5.5%	2.19m	9.5%	2.19m	9.5%
	5	1.92m	4%	1.74m	13%	1.74m	13%
	9	1.94m	3%	2.19m	9.5%	2.19m	9.5%
	37	2.26m	13%	2.19m	9.5%	2.67m	33.5%
4m	1	3.17m	20.75%	3.17m	20.75%	3.17m	20.75%
	3	4.69m	17.25%	4.29m	7.25%	3.80m	5%
	5	4.29m	7.25%	3.71m	7.25%	3.71m	7.25%
	9	4.83m	20.75%	4.89m	22.25%	4.89m	22.25%
	37	4.56m	14%	4.29m	7.25%	3.71m	7.25%
8m	1	7.72m	3.50%	7.72m	3.50%	7.72m	3.50%
	3	7.20 m	10%	6.95m	13.12%	6.95m	13.12%
	5	8.03m	0.37%	8.53m	6.62%	6.95m	13.12%
	9	7.98m	0.25%	7.72m	3.5%	6.95m	13.12%
	37	7.97m	0.37%	7.72m	3.5%	7.72m	3.5%
11m	1	8.53m	22.45%	8.53m	22.45%	8.53m	22.45%
	3	13.68 m	24.36%	13.31m	21%	-	-
	5	11.44m	4%	13.31m	21%	7.72m	29.81%
	9	11.46m	4.18%	13.31m	21%	14.43m	31.18%
	37	10.62m	3.45%	10.29m	6.45%	7.72m	29.81%
14m	1	12.25m	12.50%	12.25m	12.50%	12.25m	12.50%
	3	16.42 m	17.28%	16.84 m	20.28%	16.84 m	20.28%
	5	15.60m	11.42%	15.60m	11.42%	15.60m	11.42%
	9	16.56m	18.28%	16.84m	20.28%	16.84m	20.28%
	37	16.07m	14.78%	15.60m	11.42%	15.60m	11.42%

"Hi! I want to talk to you but you are 13.6 meters away so I cannot understand you properly". This means that, from the HRI point of view, it is not necessary to obtain the exact distance between the robot and the objects, but it is important to define the zone they are located in.

In this sense, we have considered the distances which are relevant during interpersonal interactions and, inspired by previous works in HRI (Walters et al., 2005), we have defined four possible zones related to the robot:

(1) Immediate: less than 0.5 meters.
(2) Near: between 0.5 and 8 meters.
(3) Far: more than 8 meters.
(4) Unknown: out of range.

With this in mind, the distance estimation given by our system is good enough to assign each identified object to one of this four interpersonal zones.

Nevertheless, when dealing with moving objects and people moving around, due to the considered heuristic ($1.5s$ window), fast movements between zones can lead to a wrong localization. For example, if a user changes from zone 2 to zone 1 and then back to zone 2 in less than 1.5 seconds, our method might localize that user in any of both zones. However, considering the application field of our system, i.e. human-robot interaction, most of the times a user approaches the robot to perform a social interaction, it takes much longer that 1.5 seconds and therefore this situation barely will happen. Notice that if an object or user is moving inside one of the four predefined zones, the moving rate does not alter our estimation.

5 Illustrating the benefits of BLE beacons in Social Robotics

In this section we illustrate the benefits of EBs in social robotics from two perspectives. The first one (Section 5.1) is an example of application where EBs provide information to the dialog management system of a social robot. The second one (Section 5.2) is a case study to exemplify how human-robot interactions can be improved with the real-time information about the interpersonal zones where people and objects are at.

5.1 Example of application: Using EBs in our dialog management system

The system reported here **has been** used to extend the Robotics Dialog System (RDS) presented by the authors in a previous work (Alonso-Martin, 2014). The RDS has been applied to multiple social robots running an Ubuntu OS and using the middle-ware Robotic Operating System (ROS) (Quigley et al., 2009). The RDS is in charge of handling the multimodal dialogs between a person and a robot: based on different sources of information (e.g. the person's pose, an utterance, or the distance to an object), the robot generates the

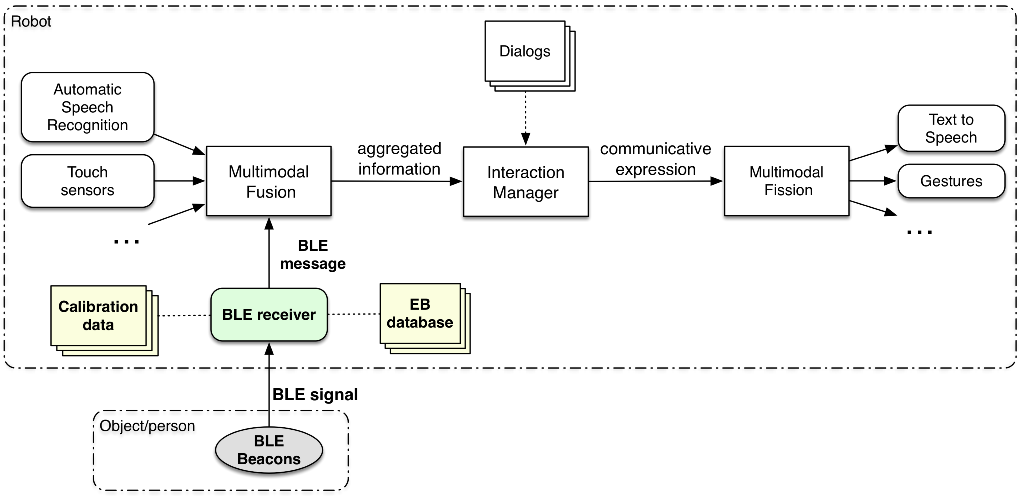

Fig. 2. The Robotics Dialog System extended with EBs as a new input source. Colored shapes represent the new elements added in this work. Rectangles refer to the main modules: multimodal fusion, multimodal fission, and Interaction Manager

appropriate communicative expressions (e.g. asking for an object the robot is pointing at). In this application, the RDS has been extended by including EB as a new source of information. That is, using EBs the robot considers the objects (and users) around it and their zone (immediate, near, far, or unknown) during its multimodal dialogs with people.

Figure 2 shows the general scheme of the RDS, including the EB system.

The RDS is a rule-based engine which has a set of predefined dialogs. Each dialog contains the rules to manage the human-robot interaction for a particular situation. The flow of the interaction during this dialog varies depending on the inputs from the users and the environment. Seeing that our system is multimodal, different kind of communication channels are considered (e.g. artificial vision system, automatic speech recognition, or touch). All the inputs are temporally aggregated in the *Multimodal Fusion* process. The result of this process is fed into the *Interaction Manager* which, based on the information received, will guide the interaction flow and generate different communicative expressions (CE). CEs are executed by the *Multimodal Fission* module which combines several output interaction channels (e.g. utterances, nonverbal sounds, gestures, or images on a screen) to transmit the right message in a proper way.

In order to clearly illustrate the operation of the RDS, imagine a dialog named *obtaining age* which is in charge of asking and obtaining a user's age. Initially, the robot starts the dialog by issuing the *greeting* CE, where the robot says *"hello"* and waves its arms.

Code Listing 1. ROS message published when an EB has changed its zone

```
string name      // For example, Fernando or Teddy

string type      // Type of object: human or item
string HUMAN = "Human"
string ITEM = "Item"

string zone      // immediate (<0.5m), near(0.5-8m), far(>8m)
    ↪ , unknown
string IMMEDIATE =  "immediate"
string NEAR = "Near"
string FAR = "Far"
string UNKNOWN = "Unknown"
```

After that, the robot uses other CE to ask about his age and waits for an answer. The user can reply by voice or entering his/her age through a touch screen. Once the user has informed about his/her age, the robot executes the *thanks* CE and the *goodbye* CE. If the user does not reply within a time frame, it will be asked again. If the user keeps on refusing to answer, the robot will execute the *goodbye* CE and the *obtaining age* dialog is ended.

In this application, the RDS has been extended to consider the zone where objects and people are located. How EB are included in the RDS is shown in the colored boxes in Figure 2. Note that EBs are attached to objects and people we want our robot to detect; the rest of the modules run inside the robot. Starting from the bottom, a BLE beacon **(gray oval) emits a periodical signal that can be recognized by the robot**. When this signal is detected by the *BLE Receiver* (green rectangle) in the robot, it processes it as follow:

(1) The ID of the emitting EB is extracted from the signal.
(2) After querying the EB database, the name and type of the object attached to the EB is obtained.
(3) Considering the calibration coefficients (Section 4.1) and the arrival energy of the signal, the distance from the emitting EB to the robot is computed.
(4) Once the distance is calculated, a zone is assigned: immediate, near, or far.
(5) If the assigned zone is different from the previous one, it means that the object (or user) has changed its position or entered in the BLE range of action. Thus, a ROS message is sent to inform of this change. This ROS message is presented in Code Listing 1 and contains the name of the object, its type, and its new zone.

These ROS messages, that are sent when an EB (i.e. object or user) changes its location from one zone to another, are received by the *Multimodal Fusion* module. **This module groups it with other data coming from the other input interaction channels and send it to the *Interaction Manager***.

In order to identify users and objects, the system needs: (i) some configuration parameters, stored in a configuration file that contains all the required information to identify an advertiser and calculate its position. This file contains the protocol used (*iBeacon*, in our case), *txPower*, and the three coefficients A, B, and C; and (ii) a database that contains the relationships between the beacon ids and the object description, i.e. the type (human or item) and its name (for example, *David* or *teddy bear*). This information will be used to fill the ROS message emitted by the *BLE receiver* module.

*5.2 Case study: a children-robot **hidden toy hunt** game*

In order to clarify the implications of the system reported here from a user point of view, in this section we detail a child-robot game that makes use of the BLE beacons.

In a previous work, the authors presented a quiz game where a robot asked questions about animals; children had to answer them by picking up the right stuffed animal and approaching it to the robot's *nose* (Gonzalez-Pacheco et al., 2011). In that game, the stuffed animals had an RFID tag and the robot was equipped with an RFID reader inside the head (in the *nasal* area). During the game, we observed some limitations: the extremely short range of action of this system caused frequent false negative identifications, some children had difficulties to reach the robot's *nose* because of their height, and the robot was not able to identify the participant that answered the question.

The EB system presented in this work overcomes these limitations. **To illustrate the advantages of the implemented system in HRI scenarios, we have developed a *hidden toy hunt* game where** children have to find several soft toys that are hidden in different places and bring them to Mini (Salichs et al., 2016), a desktop robot which is equipped with the BLE receiver, (see Figure 3(a)). Moreover, to make the game more appealing, one of the soft toys is attached to Mbot's back (see Figure 3(b)). **In this game, Mbot is wandering around the game scenario acting as an appealing character and adding extra complexity to the hunt. The goal positions for Mbot are randomly selected within the game area.** Each child carries a necklace with a BLE beacon and, in the case of the toys, the advertiser is located inside their body. Figure 4 shows a possible scenario with

(a) The robot Mini during the game (b) The robot Mbot moves around with a toy on its back (c) Toys and BLE beacons

Fig. 3. Social robots, beacons, and toys used in the game

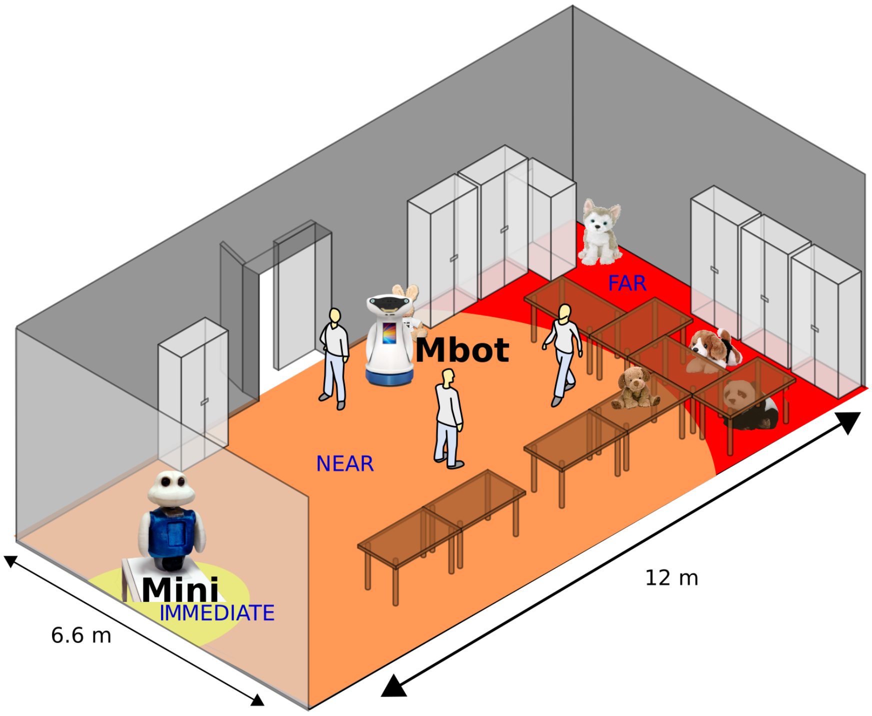

Fig. 4. Example of scenario including robots, toys, and participants. Colored areas represent the different zones: immediate (yellow), near (orange), and far (red)

the robots, the interpersonal zones in relation to Mini, and several toys and users.

Figure 5 presents the flow of the game and how EBs are used during the human-robot dialogs. We divided the game in three different phases: *Greeting* (the initial phase), *Game* (where the main part of the *hidden toy hunt* game is conducted), and *Results* (the robot notifies the results). **In the Greeting**

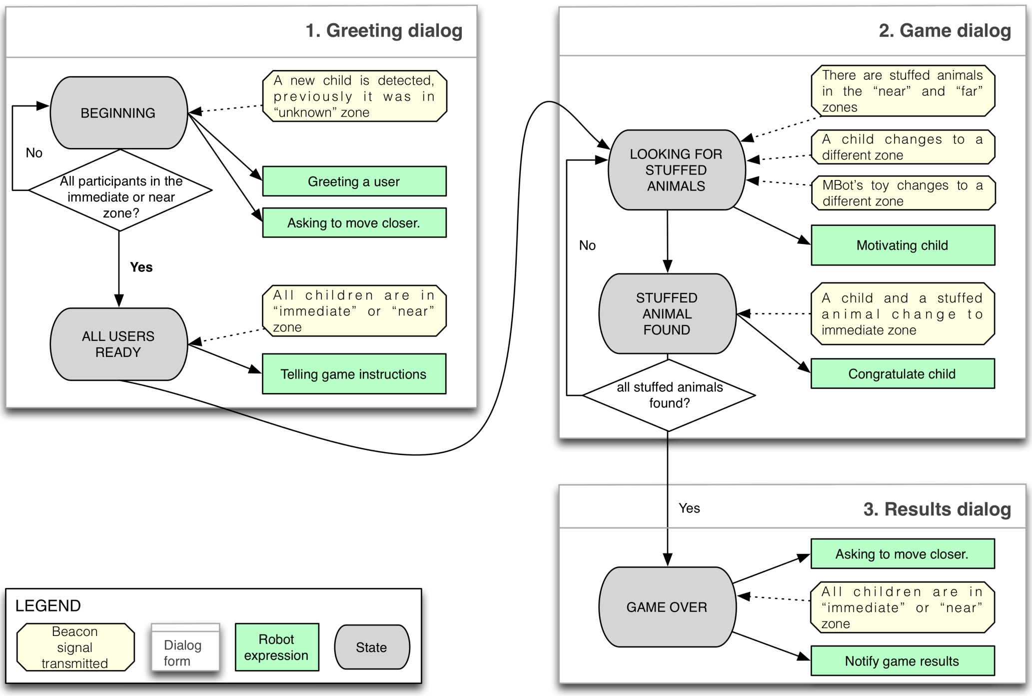

Fig. 5. Flow diagram of the dialogs in the *hidden toy hunt* game. The information provided by the BLE beacons is detailed.

phase, as children enter the immediate o near zones (shown in Fig. 4) the robot welcomes them. Once all users are within those areas, the robot explains the game rules; that is, the three children have to look for (*hunt*) 5 plushy toys that are placed (*hidden*) throughout the laboratory and on the back of Mbot. When a child finds a toy, he/she has to bring it to Mini and scores one point. After all toys are found, the game finishes, passing to the Results phase in which the robot tells the scores achieved.

For each one of these phases, we have created a dialog that manages the interaction between the children and the robot Mini. Notice that yellow hexagons in Figure 5 refer to input of information due to the use of EBs.

The interaction begins when the children step into the working range of the EBs. When this happens, Mini identifies them, localize them in the corresponding zone, and greets them. Every time a new participant appears in the surroundings of the robot, Mini greets the child using a welcome sentence like *"Hi David, I'm happy to see you! Let's play together"*. After the greetings, since Mini has to explain the game, it asks participants in the far zone (if there is anyone) to move closer (*"Please David, get closer to me"*). When all participants are in the near or immediate zone, Mini tells them the game instructions. This interaction is defined in the Greeting dialog (top box Figure 5).

After that, the game starts and the interaction is modelled in the Game dialog (middle box Figure 5). In this dialog, while children are looking for hidden soft toys, Mini encourages them by calling by their names ("Come on Diego!"), and by playing animated music or funny sounds (such as laughs, applause, etc). These motivating expressions are executed when a child changes its zone and while stuffed animals remain hidden. Besides, after a long time searching toys without success, Mini gives hints such us *"David, look for the rabbit further!"*. While the soft toy attached to MBot is not retrieved, Mini gives clues about it from time to time. For example, in case MBot moves from near to far, Mani says *"Watch out! There is an animal escaping"*.

In the course of the game, Mini identifies each toy and the child who brings it by matching the variations of the positions of the children and the toys within a certain time window. That is, if a child moves from the far/near zone to the immediate zone and, at the same time, a toy also moves in the same way, the algorithm determines that this child is carrying that toy. This algorithm may fail if, for example, two children carry the same toy. In this case, the child who moved in a most similar way than the toy would be selected. In the case that a participant finds a toy, when she hands it in to Mini, the robot congratulates the child using her name, says the name of the toy, and encourages the child to go for the remaining toys (e.g. *"Well done David! You found Donald. Let's get the next animal!"*).

Once all stuffed animals are found, the game is over and Mini summarizes the results of the game using the Results dialog (bottom box Figure 5). Here, Mini notifies the end of the game and asks all children to get closer. Once they are closer, the robot congratulates the children, plays a *happy* music, and informs about the number of stuffed animals found by each participant.

6 Conclusions

In Social Robotics, identification and localization of objects and people are two fundamental skills for getting a successful HRI. Traditionally, those processes have been carried out using systems based on artificial vision or artificial hearing, but they present several weaknesses. This paper has introduced a system based on electronic beacons for the identification and distance estimation of users and objects. After conducting a comparative analysis of the different technologies, we have found out that BLE beacons are the most appropriate for social robots.

The main advantages of the presented system are: (i) it can perform an accurate identification; (ii) it is not affected by the environmental conditions (such as light or noise); (iii) direct line of sight is not required; (iv) it is cost-efficient; (v) it does not need that the user talks or moves in order to determine its presence; and finally, (vi) the devices used are very small and light-weight.

Nevertheless, this technology also has some drawbacks. The first one is that objects and users must carry a BLE beacon, which can be perceived as a foreign object. The second one is the imprecise calculation of the distance between the advertiser and the receiver. We have shown that this rough estimation can be valid for HRI applications but it could represent a limitation for others, such as grasping. The third problem is the need of calibration. The system must be calibrated for each kind of BLE device and configuration. **For example, different models of BLE beacons will require different calibration processes; even when using the same model, differences can be found between multiple instances (although we did not observe significant differences among the multiple instances of our BLE receiver).** The location of the receiver has to be selected carefully before calibration: it should be placed in the external parts of the robot shell to avoid the signal attenuation produced by the hardware elements. Besides, if the beacons run low of battery, the energy of the signal changes and the distance estimation is significantly affected. **Also, structural elements, such as walls and doors, mitigate the received signal by the robot. Consequently, the distance estimation is affected and the BLE transmitter (person or object) is located farther than where it actually is. Therefore, assessing the effect of structural elements in the detection is an important matter that, although out of the scope of the current paper, we intend to carry out as a future work. We believe those results might be interesting for the community.** The last main drawback is related to the delay caused during the distance calculation. This is caused by the **heuristic** selected: the transmission frequency of the beacons and the number of readings considered to perform the distance estimation. Considering previous studies in HRI, we set this delay to 1.5 seconds as a compromise between the quality of the HRI and an accurate enough distance estimation. In other applications or scenarios, where the distance estimation is not relevant and the operation of beacons for long periods is not a matter, the system could be configured to work with just one reading and the transmission frequency could be increased, for example, to 5 times per second. In this case, the robot would be able to make the identification every $0.2s$.

Although this technology has some drawbacks, we believe that the use of BLE beacons in social robots has more advantages than disadvantages. Specially, in applications were social robots must be small, light, with a long battery life, and low cost. In order to show this benefits, we have presented an example of application where a robotics dialog system uses the information provided by the EBs. Besides, we have detailed a case study where a robot enriches the interaction thanks to the information provided by the EBs. This case study, where children and robot interact during a game, shows the usefulness and advantages of BLE beacons in HRI, as well as their potential for other applications.

The semantic information regarding the zones (immediate, near, far) and the objects detected (toy, child) are input in our Dialog Management System (a rule-based engine), which integrates these inputs with a priori knowledge to produce natural interactions. These interactions are then used in the case study where human-robot interaction becomes a keystone.

Acknowledgements

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References

Alam, M., Pathak, N., & Roy, N. (2015). Mobeacon: an iBeacon-assisted smartphone-based real time activity recognition framework. In *Proceedings of the 12th international conference on mobile and ubiquitous systems: computing, networking and services.* (pp. 1–10). Coimbra (Portugal).

Alliance, Z. (2009). IEEE 802.15. 4, ZigBee standard.

Alliance, Z.-W. (2015). Z-wave. http://z-wavealliance.org. [Online; accessed 01-Feb-2017].

Alonso-Martin, F. (2014). *Sistema de Interacción Humano-Robot basado en Diálogos Multimodales y Adaptables.* PhD thesis, Universidad Carlos III de Madrid.

Alonso-Martín, F., Gorostiza, J., Malfaz, M., & Salichs, M. (2012). User Localization During Human-Robot Interaction. *Sensors*, 12(7), 9913–9935.

Alonso-Martin, F., Ramey, A., & Salichs, M. Á. (2014). Speaker identification using three signal voice domains during human-robot interaction. In *Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction - HRI '14* (pp. 114–115). Bielefeld (Germany): ACM Press.

Boccadoro, M., Martinelli, F., & Pagnottelli, S. (2010). Constrained and quantized Kalman filtering for an RFID robot localization problem. *Autonomous Robots.*

Bogun, I., Angelova, A., & Jaitly, N. (2015). Object Recognition from Short Videos for Robotic Perception. (pp.7̃).

Castillo, J. C., Serrano-Cuerda, J., Fernández-Caballero, A., & Martínez-Rodrigo, A. (2016). Hierarchical architecture for robust people detection by fusion of infrared and visible video. In *Intelligent Distributed Computing IX* (pp. 343–351). Springer.

Chia-How Lin, Su-Hen Yang, Hong-Tze Chen, & Kai-Tai Song (2008). Mobile robot intruder detection based on a Zigbee sensor network. In *2008 IEEE International Conference on Systems, Man and Cybernetics* (pp. 2786–2791).: IEEE.

Cho, H.-s., Ji, J., Chen, Z., Park, H., & Lee, W. (2015). Accurate Distance Estimation between Things: A Self-correcting Approach. *Open Journal of Internet Of Things (OJIOT)*, 1(2), 19–27.

Corrales, A., Rivas, R., & Salichs, M. A. (2008). Sistema de identificación de objetos mediante RFID para un robot personal. In *Jornadas de Automática.* (pp. 978–84).

Correa, M., Hermosilla, G., Verschae, R., & Ruiz-del Solar, J. (2011). Human Detection and Identification by Robots Using Thermal and Visual Information in Domestic Environments. *Journal of Intelligent & Robotic Systems*, 66(1-2), 223–243.

Cuadra-Troncoso, J. (2015). Towards Robot Localization Using Bluetooth Low Energy Beacons RSSI Measures. In Springer (Ed.), *International Work-Conference on the Interplay Between Natural and Artificial Computation* (pp. 222–231). Elche (Spain): Springer.

Deordica, B. & Alexandru, M. (2014). Advertisement using Bluetooth Low Energy. *Review of the Air Force Academy*, 2(26), 65.

Deyle, T., Reynolds, M., & Kemp, C. (2010). RFID-Guided Robots for Pervasive Automation. *IEEE Pervasive Computing*, 9(2), 37–45.

Di Marco, D., Koch, A., Zweigle, O., Haussermann, K., Schiessle, B., Levi, P., Galvez-Lopez, D., Riazuelo, L., Civera, J., Montiel, J., Tenorth, M., Perzylo, A., Waibel, M., & van de Molengraft, R. (2012). Creating and using RoboEarth object models. In *2012 IEEE International Conference on Robotics and Automation* (pp. 3549–3550).: IEEE.

Dilger, D. (2013). Inside iOS 7: iBeacons enhance apps' location awareness via Bluetooth LE. *ed: Apple Insider.2013.2013.*

Dondrup, C., Bellotto, N., Jovan, F., & Hanheide, M. (2015). Real-time multi-sensor people tracking for human-robot spatial interaction. In *International Conference on Robotics and Automation (ICRA) - Workshop on Machine Learning for Social Robotics.*

Faragher, R. & Harle, R. (2014). An Analysis of the Accuracy of Bluetooth Low Energy for Indoor Positioning Applications. In *Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2014)* (pp. 201 – 210). Florida.

Fernández-Caballero, A., Castillo, J. C., Martínez-Cantos, J., & Martínez-Tomás, R. (2010). Optical flow or image subtraction in human detection from infrared camera on mobile robot. *Robotics and Autonomous Systems*, 58(12), 1273–1281.

Ganick, A. & Ryan, D. (2012). Light positioning system using digital pulse recognition.

García, D., Pallardó, C., Insua, D., Moreno, R., & Redchuk, A. (2011). AIsoy 1: A Robot that Perceives, Feels and Makes Decisions. *ERCIM News*.

Gonzalez-Pacheco, V., Ramey, A., Alonso-Martin, F., Castro-Gonzalez, A., & Salichs, M. A. (2011). Maggie: A Social Robot as a Gaming Platform. *International Journal of Social Robotics*, 3(4), 371–381.

Hall, E. (1966). The hidden dimension. *Garden City, N.Y*, Doubleday.

Jeffus, B., Zeltmann, S., Griffin, K., & Chen, A. (2015). The Future of Mobile Electronic Payments. *Competition Forum*, 13(2), 337.

Jin, M.-H., Yu, C.-H., Lai, H.-R., & Feng, M.-W. (2007). Zigbee Positioning System for Smart Home Application. In P. Thulasiraman, X. He, T. L. Xu, M. K. Denko, R. K. Thulasiram, & L. T. Yang (Eds.), *Chapter Frontiers of High Performance Computing and Networking ISPA 2007 Workshops*, volume 4743 of *Lecture Notes in Computer Science* (pp. 183–192). Berlin, Heidelberg: Springer Berlin Heidelberg.

Kehoe, B., Matsukawa, A., Candido, S., Kuffner, J., & Goldberg, K. (2013). Cloud-based robot grasping with the google object recognition engine. In *2013 IEEE International Conference on Robotics and Automation* (pp. 4263–4270).: IEEE.

Kulyukin, V. & Gharpure, C. (2004). RFID in robot-assisted indoor navigation for the visually impaired. In IEEE (Ed.), *Proceedings. 2004 IEEE/RSJ International Conference on* (pp. 1979–1984). Sendai (Japan): IEEE.

Medina, C. & Navarro, M. (2015). LED based visible light communication: technolgy, applications, and challengnes. A survey. *International Journal of Advances in Engineering & Technology*, 8(4), :482–495.

Min Huasong, Liu Zhenglin, Wei Hongxing, & Wang Tianmiao (2010). Control of a self-assembly modular robot system over a wireless ZigBee network. In *2010 8th World Congress on Intelligent Control and Automation* (pp. 1057–1062).: IEEE.

Mohanarajah, G., Hunziker, D., D'Andrea, R., & Waibel, M. (2015). Rapyuta: A Cloud Robotics Platform. *IEEE Transactions on Automation Science and Engineering*, 12(2), 481–493.

Nakadai, K. & Takahashi, T. (2010). Design and Implementation of Robot Audition System 'HARK'. Open Source Software for Listening to Three Simultaneous Speakers. *Advanced Robotics*, 24(5-6), 739–761.

Navarro-Serment, L. (1999). A beacon system for the localization of distributed robotic teams. In IEEE (Ed.), *International Conference on Field and Service Robotics* (pp. 1–6). Pittsburgh: IEEE Press.

Newman, N. (2014). Apple iBeacon technology briefing. *Journal of Direct, Data and Digital Marketing Practice*, 15(3), 222–225.

Ok, K. & Coskun, V. (2010). Current benefits and future directions of NFC services. In *In Education and Management Technology (ICEMT)* (pp. 334–338).

Olivares, T., Tirado, P. J., Royo, F., Castillo, J. C., & Orozoco-Barbosa, L. (2007). Intellbuilding: A wireless sensor network for intelligent buildings. In *proceedings of the 4th European Conference EWSN*: Citeseer.

Ortiz, A. M., Royo, F., Olivares, T., Castillo, J. C., Orozco-Barbosa, L., & Marron, P. J. (2013). Fuzzy-logic based routing for dense wireless sensor networks. *Telecommunication Systems*, 52(4), 2687–2697.

P, R. & Sichitiu, M. (2006). Angle of Arrival Localization for Wireless Sensor Networks. In *2006 3rd Annual IEEE Communications Society on Sensor and Ad Hoc Communications and Networks*, volume 1 (pp. 374–382).: IEEE.

Quigley, M., Conley, K., Gerkey, B., Faust, J., Foote, T., Leibs, J., Wheeler, R., & Ng, A. Y. (2009). Ros: an open-source robot operating system. In *ICRA workshop on open source software*, volume 3 (pp.$\tilde{5}$).: Kobe.

Rashid, M. T., Ali, A. A., Ali, R. S., Fortuna, L., Frasca, M., & Xibilia, M. G. (2012). Wireless underwater mobile robot system based on ZigBee. In *2012 International Conference on Future Communication Networks* (pp. 117–122).: IEEE.

Roberts, C. (2006). Radio frequency identification (RFID). *Computers & Security*, 25(1), 18–26.

Rontidis, G., Panaousis, E., Laszka, A., Dagiuklas, T., Malacaria, P., & Alpcan, T. (2015). A game-theoretic approach for minimizing security risks in the Internet-of-Things. In *2015 IEEE International Conference on Communication Workshop (ICCW)* (pp. 2639–2644).: IEEE.

Salichs, M. A., Encinar, I. P., Salichs, E., Castro-González, Á., & Malfaz, M. (2016). Study of scenarios and technical requirements of a social assistive robot for alzheimers disease patients and their caregivers. *International Journal of Social Robotics*, 8(1), 85–102.

Schwarz, D., Schwarz, M., Stückler, J., & Behnke, S. (2015). Cosero, find my keys! Object localization and retrieval using Bluetooth Low Energy tags. In S. I. Publishing. (Ed.), *RoboCup 2014: Robot World Cup XVIII* (pp. 195–206). Joao Pessoa (Brazil): Springer International Publishing.

Seybold, . J. S. (2005). *Introduction to RF propagation.* New York, NY, US.

Shiwa, T., Kanda, T., Imai, M., Ishiguro, H., & Hagita, N. (2009). How quickly should a communication robot respond? delaying strategies and habituation effects. *International Journal of Social Robotics*, 1(2), 141–155.

Silva, S., Soares, S., Fernandes, T., Valente, A., & Moreira, A. (2014). Coexistence and interference tests on a Bluetooth Low Energy front-end. In *2014 Science and Information Conference* (pp. 1014–1018).: IEEE.

Smith, P. (2015). Augmenting Reality in Sensor Based Training Games. *Virtual, Augmented and Mixed Reality.*

Technologies, G. (2016). ZigBee compared with Bluetooth Low Energy.

Walters, M. L., Dautenhahn, K., Te Boekhorst, R., Koay, K. L., Kaouri, C., Woods, S., Nehaniv, C., Lee, D., & Werry, I. (2005). The influence of subjects' personality traits on personal spatial zones in a human-robot interaction experiment. In *Robot and Human Interactive Communication, 2005. ROMAN 2005. IEEE International Workshop on* (pp. 347–352).: IEEE.

Wang, H., Yu, K., & Yu, H. (2010). Mobile robot localisation using ZigBee wireless sensor networks and a vision sensor. *International Journal of Modelling, Identification and Control*.

Want, R. (2011). Near field communication. *IEEE Pervasive Computing*, 10(3), 4–7.