Comparison between UHF RFID and BLE for stereo-based tag association in outdoor scenarios

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***Abstract*—Stereo-based object detection systems can be greatly enhanced thanks to the use of wireless identification technology. By combining tag localization with its identification capability, new features can be associated with each detected object, extending the set of potential applications. The main problem consists in the association between wireless tags and objects due to the intrinsic limitations of Received Signal Strength Indicator-based localization approaches. In this paper, an experimental comparison between two specific technologies is presented: passive UHF Radio Frequency IDentification (RFID) and Bluetooth Low Energy (BLE). An automatic calibration process is used to model the relationship between RSSI and distance values. A robust data association method is presented to deal with complex outdoor scenarios in medium sized areas with a measurement range up to 15m. The proposed approach is validated in crosswalks with pedestrians wearing portable RFID passive tags and active BLE beacons.**

I. INTRODUCTION

The use of radio frequency identification is emerging as one of most fundamental technologies due to its localization and identification capabilities. It has achieved a widespread success in various applications ranging from asset tracking, highway toll collection, supply chain management, animal identification, surveillance systems, aerospace, etc. [1], [2]. More specifically, passive Ultra High Frequency technology has attracted a great attention from both industry and academia due to the fact that a built-in power source in the tag is not needed. The passive tag can communicate with the reader thanks to the use of backscattered coupling from the tag to the reader. In addition, BLE (or Bluetooth Smart) provides a high communication range at a reduced power consumption and a minimum cost. Although powered active beacons [1] are needed in this case, they are small enough to be used in many different applications. By modeling the Received Signal Strength Indicator (RSSI) a rough estimation of the relative position between the tag and the antenna can be obtained. When more than one (non-isotropic) or two (isotropic) antennas are available, different multilateration techniques can be applied to compute the global position of the tagged objects (RSSI localization). However, the accurate and robust estimation of the physical location of tagged objects is still a challenging task due to the intrinsic limitations and directional dependence when using RSSI as a distance metric [3], [4]. When other sensors are available, different fusion schemes can be used to

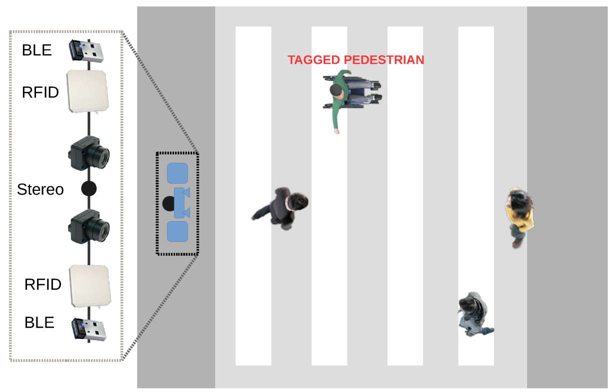

Fig. 1. Pedestrian crossing scenario. Only one (a maximum or two) pedestrians are tagged. The system needs to associate the detected tag with the corresponding pedestrian.

improve localization [5], [6]. However, if the accuracy of the range measurements given by such other sensors (for example, vision- or laser-based systems) is much better than the one provided by RSSI-based systems, then RSSI localization is only performed to solve the data association problem, linking tags with objects, and considering the physical location of the tagged object as the one given by the other sensors [7], [8].

In this paper, an experimental comparison between passive UHF RFID and active BLE radio frequency identification technologies is proposed within the context of stereo-RSSI data association in outdoor scenarios. A rough estimation of the location of the tagged object is obtained by means of a RSSI-distance model with parameters that are automatically computed by applying an automatic stereo-RSSI calibration process. A robust data association method based on a global nearest neighbor (GNN) and a new distance metric is presented to deal with complex outdoor scenarios in medium sized areas with a range up to 15m. To validate and compare both technologies an intelligent pedestrian crossing application is used as an example (see Fig. 1). A stereo-based pedestrian detection system [9] provides accurate locations of pedestrians that may carry portable RFID/BLE tags. The most typical scenario involves several pedestrians crossing, but only one or two carrying a tag. The infrastructure has to estimate the tagged pedestrian among all the tracked ones to efficiently provide an adaptive response to users with disabilities [8].

[1]From now on, BLE active beacons will be named as BLE tags.

II. RELATED WORK

Object localization based on radio frequency identification technology has been widely proposed to address a considerable number of different applications [6], including different technologies such as RFID, Ultra-Wide Band (UWB), Bluetooth, BLE, ZigBee, WiFi, etc. [5], and different RSSI-based localization approaches such as multilateration, Bayesian inference, nearest-neighbor and proximity [6]. A considerable number of works have been proposed for the localization of radio-frequency tags (objects) with fixed nodes (antennas), as well as the localization of moving nodes using a fixed set of tags [5]. However, for the course of this work, we focus on the localization of moving passive tags using fixed or moving nodes in combination with vision-based approaches.

In most cases, the combination of wireless sensors and vision-based localization techniques is used to increase the global localization accuracy by means of some Bayesian filter (Kalman Filter -KF-, Extended KF -EKF-, Particle Filter -PF-, Unscented Kalman Filter -UKF-, etc.), that fuses the range measurements coming from the different sensors. Thus, in [10], eight directive RFID antennas, and one camera are embedded on a mobile robot to detect passive tags worn on the user's clothes, in indoor environments with a range of 5m. Saliency maps are obtained for each antenna by counting occurrence frequencies, and translated to the image domain. These maps are used to filter particles on a PF applied over a skin probability image. In [11], RFID-based localization in a small indoor area of interest with a limited number of objects is carried out via RSSI measurements and combined with a camera-based localization by means of an UKF. There is an obvious improvement in the RFID-based localization accuracy thanks to the use of the monocular vision system. The formula between RSSI measurements and distance is adjusted using a manual calibration process. No data association is performed since results are provided only with one object that is directly associated with the detected tag. A similar fusion scheme using a Particle Filter (PF) to combine RSSI data from passive RFID tags with stereo measurements is proposed in [12]. Four different antennas are used to cover an indoor region of 4×4 meters. RSSI-distance calibration procedure involves manual distance computation, and a linear-regression model is used to obtain distance from RSSI measurements. Multilateration is used to perform RSSI-based localization. Again, no data association is applied since only one object is taken into account. PF is also applied in [13] to fuse WiFi and vision measurements in outdoor scenarios. The so-called fingerprints (SSID and RSSI of different nodes) and a GPS are used to perform RSSI-distance calibration. The GPS is only used for calibration, and its accuracy is limited when no differential corrections are available. RSSI-based localization is carried out using the centroid position of all the access points. Data association is not applied since results are obtained using only one person.

An interesting dynamical RSSI-distance calibration process is proposed in [14] using linear local models around the target, combining RSSI and vision measurements using an Extended Information Filter (EIF) in indoor environments. Although the dynamic RSSI model increases localization accuracy, its use is limited to one-object one-tag scenario. In real scenarios with multiple targets, perfect data association will be needed. A room-level accuracy system is proposed in [15], by means of a RSSI-room calibration process and a video tracking system able to detect a person entering/leaving a room. Trilateration is then applied to solve the room-level localization problem. Results are provided with only one candidate so no data association process is applied.

As can be observed, and suggested by [16] and [8], data association problem between objects or blobs and tags has been somehow neglected in the literature, which limits the applicability to real scenarios. [16] proposed a probabilistic framework to combine RFID and monocular vision measurements for indoor scenarios in a limited range. A predefined and manual grid is used to perform RSSI-distance calibration, modeling each grid position with a Gaussian distribution. RSSI-based localization is solved by means of a Mixture of Gaussians, where each mode corresponds to one RFID antenna. A Hidden Markov Model is finally applied to deal with the data association problem using a Gaussian distribution as a metric, and finally combining RSSI and vision measurements to compute the person/tag final position.

However, as suggested by several studies [3], [4] there are intrinsic limitations when using RSSI as a distance metric in terms of accuracy and stability for localization purposes. Thus, as in [7], we propose to use the RFID/BLE systems as an identification tool, and the vision system [9] for localization. Thus the data fusion problem can be translated into a pure data association problem. A global nearest neighbor (GNN) algorithm with a novel distance metric is proposed to link radio frequency tags with stereo objects (pedestrians). Our RSSI-distance calibration process is fully automatic. The system is devised to be used in outdoor scenarios (crosswalks), in medium sized areas with a measurement range up to 15m, which is a clear contribution w.r.t. the state of the art.

III. RSSI-BASED LOCALIZATION

In most RSSI-based localization approaches, the signal strength received by a sensor from another one is considered as a monotonically decreasing function of their distance (standard approach). As described in [4], a simplified form of the relation between distance and receive power has been mostly used:

$$P_r(dBm) = P_{r1}(dBm) - K.log_{10}(D(m)) \quad (1)$$

where P_{r1} is the received power in dBm at $1m$, K is the loss parameter and D is the distance between the receiver and the transmitter. The values of P_{r1} and K are determined by minimizing the root mean square error using calibration data, i. e., RSSI and ground-truth distance measurements.

Thanks to the stereo-based object detection system [9] the calibration data including thousand of RSSI and distance measurements can be automatically obtained. Stereo reconstruction provides 3D points P_{LC} referenced to the left camera

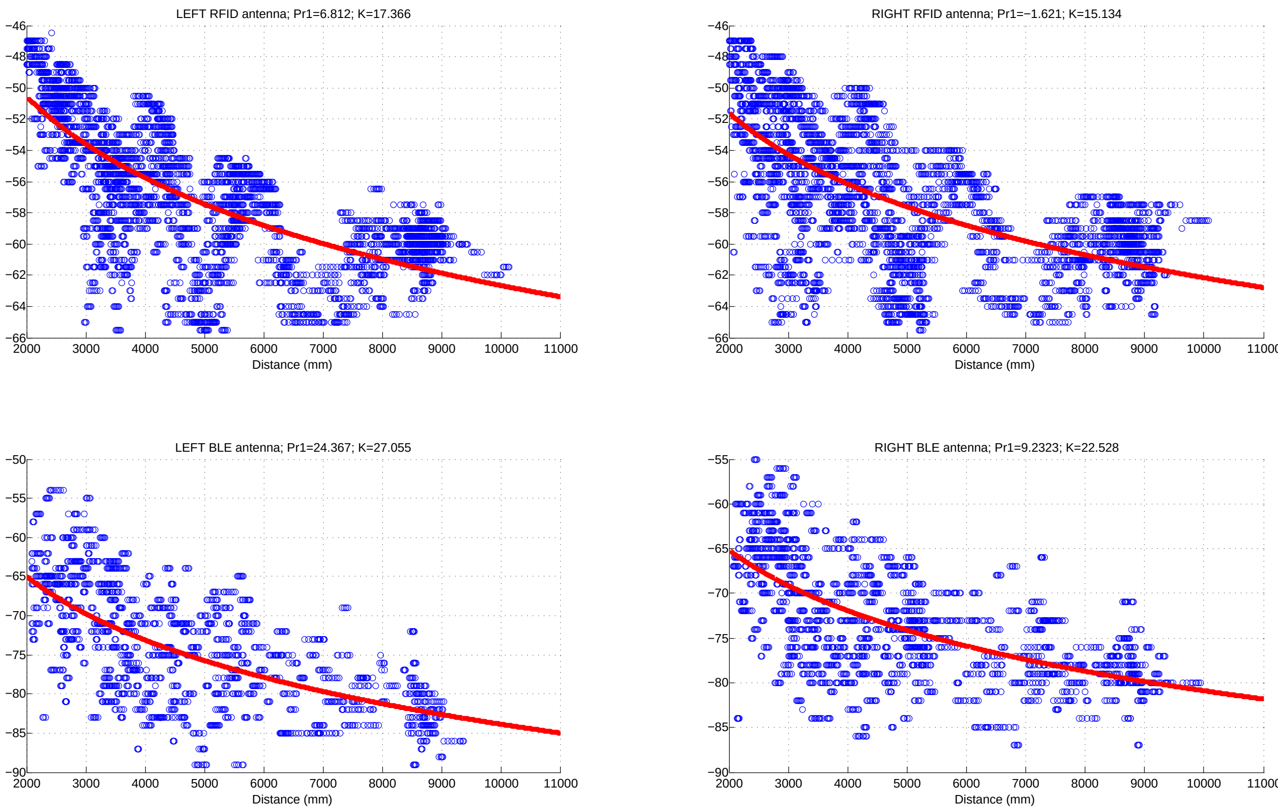

Fig. 2. RSSI-distance model. Upper row: passive UHF RFID. Lower row: BLE. Left and right antennas respectively.

(*LC*). The relative positions of both the left and the right antennas (*LA*; *RA*) w.r.t. the left camera are approximated by using an identity rotation matrix and translation vectors only containing the X component. Thus, points P_{LA} and P_{RA} can be easily computed and associated with their corresponding RSSI values. By using a sequence of one person carrying one tag in a fixed position and orientation, and moving around the stereo region, the stereo-based pedestrian location system can be applied to get 3D measurements w.r.t. one reference point. These measurements can be directly associated with the RSSI values given by the antennas since data association is not needed at this stage (one person-one tag). The 3D position of the tag w.r.t. the stereo system is approximated as the center of the 3D blob assuming a fixed tag height w.r.t. the road plane.

After applying the automatic calibration procedure, we obtain the parameters of Eq. 1 and the RSSI-distance curves depicted in Fig. 2 for both RFID and BLE, and the left and right antennas respectively. In addition, we compute the exact variance as a function of the RSSI-based distance, which will be used later on. For a given RSSI value (P_r), we compute the corresponding distance as $D = 10^{(P_r - P_{r1})/-K}$, and we get the associated pre-computed variance σ_D^2. The possible location of the tag/beacon w.r.t. to the antenna will then be defined as a circumference centered at the antenna position with radius D.

Finally, a Kalman filter is used to get steadier distance estimations for each tag and antenna. A constant variation model is used. The state vector includes the RSSI value and its variation, whereas the measurement vector is defined by the RSSI value. The RSSI variance is computed during the calibration process.

IV. STEREO-RSSI DATA ASSOCIATION

A single RSSI value yields a sphere with the antenna position at its center and radius equal to the RSSI-based distance measurement as possible tag locations. In our case, a fixed and known tag height is assumed to reduce the 3D sphere to a 2D circumference. Then the tag/beacon position can be determined by intersecting the circumferences generated by each antenna. For isotropic antennas with a 360° radiation pattern, a minimum of 3 antennas are needed to compute the tag/beacon location. However, in our case, directional 180° antennas are used and one of the intersection points can be discarded. Accordingly, two antennas are enough for providing a unique solution.

However, as suggested by previous works [3], [4], and supported by our data (see Fig 2), the intrinsic limitations when using RSSI as a distance metric in terms of accuracy and stability, as well as, in our case, the suboptimal position of both antennas (at the same baseline, see Fig. 3) causes that the intersection point or area (including the uncertainties) is not a robust and accurate metric to be used for solving the data association problem. Accordingly, a new distance metric that models the probability of association between a 3D object (stereo-based) and a detected tag (RSSI-based) is proposed.

The distance d_k^{ij} between a 3D object i and the tag/beacon j (assuming fixed height) detected by antenna k ($k = LA$ for left antenna and $k = RA$ for right antenna) is modeled using a univariate normal distribution where the mean value is the RSSI-based computed distance d_k^j, the variance is the one computed after RSSI-distance calibration $\sigma^2_{d_k^j}$ and the independent variable is the 3D object position w.r.t. the antenna $d^i_{stereo,k}$:

$$d_k^{ij} = \frac{1}{\sigma_{d_k^j}\sqrt{2\pi}} e^{-\frac{(d^i_{stereo,k} - d_k^j)^2}{2\sigma^2_{d_k^j}}} \tag{2}$$

The graphical representation of this metric is depicted in Fig. 3. Eq. (2) is computed for both antennas. If one of them does not receive signal, the metric would be set to zero. In order to compute the global metric d^{ij} that represents the probability that tag j is being worn by person i, the following equation would be applied:

$$d^{ij} = d^{ij}_{LA} . d^{ij}_{RA} \tag{3}$$

This approach can be easily extended to N antennas by applying the following equation:

$$d^{ij} = \prod_{k=1}^{N} d_k^{ij} \tag{4}$$

To achieve a reliable data association, a global nearest-neighbor (GNN) [17] algorithm is applied. The association probability between the predicted position of all pedestrians ($i = 1 \dots P$) and all the detected tags ($j = 1 \dots T$) are computed at each time iteration t. The corresponding probability matrix C is defined using the computed distances d^{ij}. The Hungarian or Munkres algorithm is then applied so that the global association probability is maximized, as long as the final assignment is always greater than 0.5. A higher/lower threshold would increase/decrease delays and false negatives, decreasing/increasing the number of incorrect associations. In order to avoid oscillations between the associations, a variable c^{ij} is used for each 3D object i accounting the number of times it has been associated with tag j. The final association at time t is given by the 3D object i that holds the maximum number of associations. When this counter achieves a maximum threshold, the association is fixed until the tag/beacon or the 3D object leaves the detection area.

V. Experimental Results

The stereo-based object detection system developed by our group, has been previously validated in different types of scenarios [8] (daytime and nighttime), with an average Detection Rate (DR) of 99% at a False Positive Rate (FPR) of 1.5%. In addition, the 90% of the objects detected by the system were tracked in less than 10 frames after they were fully visible (0.33 seconds).

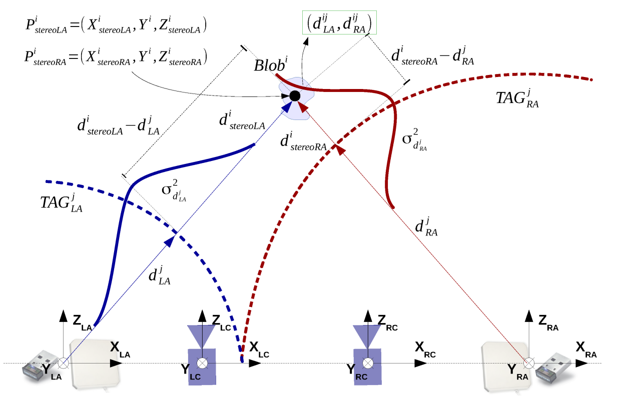

Fig. 3. Graphical representation of the new metric defined between a 3D object and the tag detected by both antennas.

In order to validate the proposed methodology, different types of sequences have been recorded in a crosswalk scenario, including different number of people, tags and trajectories in daytime and dry weather conditions. Some users were required to carry one tag at a fixed height and pointing to the antennas. Other users were only required to cross the road as usual. In order to validate the proposed methodology, the following metrics are used: percentage of time that the tag is correctly associated (CA, Correct Association) and percentage of time a tag has not been associated (NA, Not Associated). Due to the nature of our problem, a tag associated to a wrong pedestrian for cases in which the pedestrian is really close to the tagged one can be considered as correct associations. Accordingly, we also compute the percentage of time the tag is correctly associated or associated to a near pedestrian walking or waiting in parallel (CNA, Correct-Near Association). We provide results corresponding to both RFID and BLE technologies in Table I.

As can be observed BLE technology outperforms the results given by RFID in most cases. Considering all the sequences, average metrics are: $CA_{RFID} = 74,8\%$, $CA_{BLE} = 70,3\%$, $CNA_{RFID} = 81,1\%$, $CNA_{BLE} = 89,8\%$, $NA_{RFID} = 14,7\%$, $NA_{BLE} = 5,4\%$. The percentage of time a tag is not assigned is considerably lower for BLE than for RFID. RFID reports better CA performance when discriminating between parallel pedestrians which involves a better lateral discrimination capability. However, if we consider CNA metric, BLE reports a considerable increase ($8,7\%$) in the percentage of time a tag is correctly associated or associated to a near object. Some examples are depicted in Fig. 4.

VI. Conclusion

An experimental comparison between RFID and BLE technologies for dealing with stereo-RSSI data association in outdoor scenarios has been presented. RFID provides a better sensitivity when discriminating tagged objects in parallel. However, BLE reports better percentages of correct association in most cases, and a lower rate of non-associated tags. If the application is robust to tag-object associations between close

TABLE I
STEREO-RSSI DATA ASSOCIATION RESULTS.

Sequence Description	**Duration (frames)**	**CA (%) RFID / BLE**	**CNA (%) RFID / BLE**	**NA (%) RFID / BLE**
Calibration	8230	99,4 / 100,0	99,4 / 100,0	0,6 / 0,0
One Tagged Pedestrian Crossing	3270	87,5 / 98,0	87,5 / 98,0	12,5 / 2,0
One Tagged / One Non-tagged Pedestrians Opposite Crossing	2710	67,0 / 90,0	67,0 / 90,0	33,0 / 7,2
One Tagged / One Non-tagged Pedestrians Paralell Crossing	2380	68,3 / 28,4	76,5 / 98,5	23,5 / 1,5
One Tagged / Two Non-tagged Pedestrians Mixed	4740	57,1 / 70,2	84,2 / 86,2	14,4 / 4,6
Two Tagged Pedestrians Opposite Crossing	1270	59,6 / 82,1	59,6 / 82,1	35,1 / 17,9
Two Tagged Pedestrians Paralell Crossing	1250	58,1 / 44,7	58,1 / 83,9	41,9 / 16,1
One Tagged / Five Non-tagged Pedestrians Mixed	9180	62,6 / 43,0	75,5 / 79,1	8,7 / 7,0

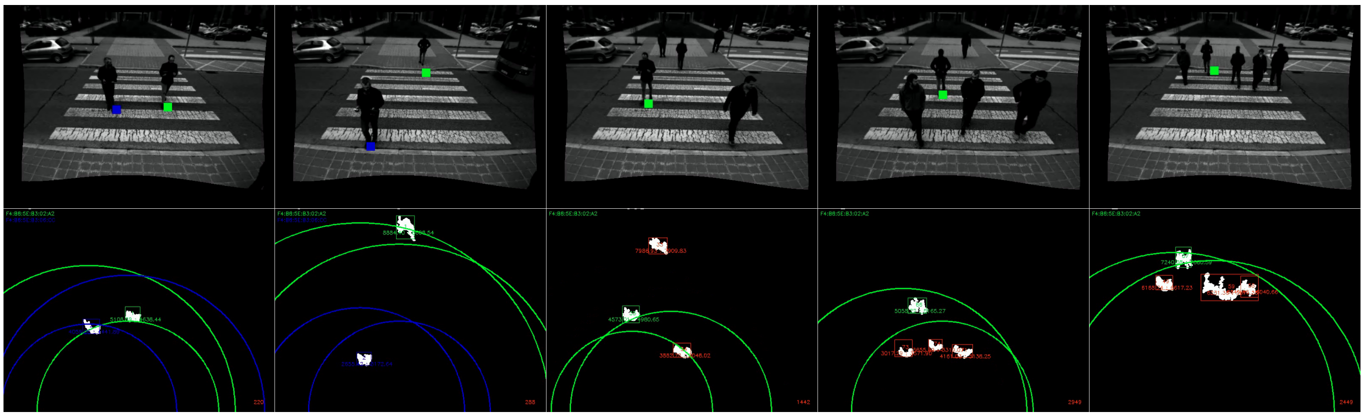

Fig. 4. Upper row: left image with color-coded identification. Lower row: XZ-map (top-view without road points), detected blobs and RSSI circumferences. Each tag is labeled with a different color.

objects moving in parallel, BLE correctly associates the tag during almost the 90% of the time which clearly validates the proposed methodology. Future works will be related with the use of more complex RSSI-distance models to enhance the performance.

VII. ACKNOWLEDGMENTS

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REFERENCES

[1] B. Nath, F. Reynolds, and R. Want, "Rfid technology and applications." *IEEE Pervasive Computing*, vol. 1, pp. 22–24, 2006.

[2] S. B. Miles, S. E. Sarma, and J. R. Williams, *RFID technology and applications*. Cambridge University Press, 2008.

[3] A. T. Parameswaran, M. I. Husa, and S. Upadhyaya, "Is rssi a reliable parameter in sensor localization algorithms an experimental study," in *Field Failure Data Analysis Workshop*, 2009.

[4] K. Heurtefeux and F. Valois, "Is rssi a good choice for localization in wireless sensor network?" in *IEEE 26th International Conference on Advanced Information Networking and Applications (AINA)*, 2012.

[5] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man and Cybernetics - Part C*, vol. 37, no. 6, pp. 1067–1080, 2007.

[6] J. Zhou and J. Shi, "Rfid localization algorithms and applicationsa review," *Journal of Intelligent Manufacturing*, vol. 20, no. 6, pp. 695–707, 2009.

[7] A. Isasi, S. Rodriguez, J. L. D. Armentia, and A. Villodas, "Location, tracking and identification with rfid and vision data fusion," in *2010 European Workshop on Smart Objects: Systems, Technologies and Applications (RFID Sys Tech)*, 2010.

[8] D. F. Llorca, R. Quintero, I. Parra, R. Izquierdo, C. Fernndez, and M. A. Sotelo, "Assistive pedestrian crossings by means of stereo localization and rfid anonymous disability identification," in *IEEE Intelligent Transportation Systems Conference (ITSC)*, 2015.

[9] D. F. Llorca, I. Parra, R. Quintero, C. Fernández, R. Izquierdo, and M. A. Sotelo, "Stereo-based pedestrian detection in crosswalks for pedestrian behavioural modelling assessment," in *ICINCO2014, International Conference on Informatics in Control, Automation and Robotics*, 2014.

[10] T. Germa, F. Lerasle, N. Ouadah, and V. Cadenat, "Vision and rfid data fusion for tracking people in crows by a mobile robot," *Computer Vision and Image Understanding*, vol. 114, pp. 641–651, 2010.

[11] T. Nick, S. Cordes, J. Gotze, and W. John, "Camera-assisted localization of passive rfid labels," in *International Conference on Indoor Positioning and Indoor Navigation*, 2012.

[12] F. Schwiegelshohn, T. Nick, and J. Gotze, "Localization based on fusion of rfid and stereo image data," in *10th Workshop on Positioning Navigation and Communication (WPNC)*, 2013.

[13] T. Miyaki, T. Yamasaki, and K. Aizawa, "Tracking persons using particle filter fusing visual and wi-fi localizations for widely distributed camera," in *IEEE International Conference on Image Processing (ICIP).*, 2007.

[14] A. de San Bernabe, J. R. M. d. Dios, and A. Ollero, "Mechanisms for efficient integration of rssi in localization and tracking with wireless camera networks," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2013.

[15] L. Radaelli, Y. Moses, and C. S. Jensen, "Using cameras to improve wi-fi based indoor positioning," *Lecture Notes in Computer Science*, vol. 8470, pp. 166–183, 2014.

[16] M. Goller, C. Feichtenhofer, and A. Pinz, "Fusing rfid and computer vision for probabilistic tag localization," in *IEEE International Conference on RFID (IEEE RFID)*, 2014.

[17] S. Blackman and R. Popoli, *Design and analysis of modern tracking systems*. Artech House, 1999.