SALT: Source-Agnostic Localization Technique Based on Context Data from Binary Sensor Networks

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Abstract. Localization is a key component for many AAL systems, since the user position can be used for detecting user's activities and activating devices. While for outdoor scenarios Global Positioning System (GPS) constitutes a reliable and easily available technology, in indoor scenarios, in particular in real homes, GPS is largely unavailable. For this reason, several systems have been proposed for indoor localization. Recently, several algorithms fuse information coming from different sources in order to improve the overall accuracy in monitoring user activities. In this paper we propose a Source-Agnostic Localization Technique, called SALT, that fuses the information (coordinates) provided by a localization system with the information coming from the binary sensor network deployed within the environment. In order to evaluate the proposed framework, we tested our solution by using a previous developed heterogeneous localization systems presented at the international competition EvAAL 2013.

Keywords: Indoor Localization · Binary Sensor Network · Sensor Fusion · Ambient Assisted Living

1 Introduction

Localization of devices and people has been recognized as one of the main building block of context aware systems [1–3], which have one of their main application field in Ambient Assisted Living (AAL) applications. It is a key component of many AAL systems, since the user position can be used for detecting user's activities, activating devices, etc. While in outdoor scenarios Global Positioning System (GPS) constitutes a reliable and easily available technology, for indoor scenarios GPS is largely unavailable. For this reason, several systems have been proposed for indoor localization. These algorithms fuse information coming from different sources in order to improve the overall accuracy in monitoring user activities. In literature, each solution has advantages and shortcomings, which,

E. Aarts et al. (Eds.): AmI 2014, LNCS 8850, pp. 17–32, 2014.
DOI: 10.1007/978-3-319-14112-1_2

in most cases, can be summarized in a trade-off between precision and installation complexity (and thus costs). In practice, although indoor localization has been a research topic for several decades, there is still not a *de-facto* standard. Moreover, localization in AAL applications has specific requirements due to the fact that AAL systems must be deployed in real homes. In particular, localization system for AAL should be well hidden, easy to install and configure, and reliable. Most of them use range-based localization methods. These systems exploit measurements of physical quantities related to beacon packets exchanged between the mobile and the anchors (devices deployed in the environment whose position is a priori known). Radio signal quantities measured are typically the Received Signal Strength (RSS), the Angle Of Arrival (AOA), the Time Of Arrival (TOA), and the Time Difference Of Arrival (TDOA). Although AOA or TDOA can guarantee a high localization precision, they require dedicated hardware. This was a major drawback, in particular for AAL applications where low price and unobtrusive hardware are required.

In this paper we propose a framework overlay that, fusing the output of an underlying localization system with context information, improves their overall precision. Usually, the context information are sensor nodes with the most elementary sensing capabilities that provide just binary information (*binary sensors*). These binary information such as open/closed doors, on/off switches, or present/not-present in beds or chairs, can be used to infer that the user is in the room where the sensor is installed or, more precisely nearby it [4]. Thus, the combination of different sensor signals of different systems produces a more accurate and robust system solution. Information collected from binary sensor networks reduces uncertainty, improves accuracy, and increases tolerance to failures in estimating the location of observed user. By combining information from many different sources, it would be possible to reduce the uncertainty and ambiguity inherent in making decisions based only on a single information source. Furthermore, the proposed system is able to provide a rough localization information in absence of a dedicated subsystem with a room-level accuracy. When the proposed technique is used in absence of a dedicated localization system, using only the context data received from the binary sensor network, it is able to provide the position in terms of last room visited by the user. This is useful in the case of AAL scenarios involving the use of assistive robots [5]. When an alarm is raised due to, e.g., a fall detection or emergency call, the caregiver can pilot the robot in the last known room occupied by the user for a prompt reaction.

Recently, an international competition, called EvAAL (*Ev*aluating *AAL* Systems through Competitive Benchmarking), has been organized in order to evaluate and compare indoor localization systems for AAL solutions [6]. In particular, the last three years EvAAL focused on evaluate several localization systems not only from the point of view of position accuracy and system reliability, but also on compatibility with existing standard, deployment effort and user acceptance [6–8]. In this work, we use the datasets coming from the EvAAL's competitors in order to show both how their performance increases using the proposed Source-Agnostic

Localization Technique (SALT) based on the binary sensor network overlay and how our system would have performed as a stand-alone system. In this way, the proposed SALT overlay is totally transparent with respect to the underlying localization systems that could be based on several signal types (infrared, ultrasound, ultra-wideband, and radio frequency), signal metrics (AOA, TOA , TDOA, and RSS), and metric processing methods (triangulation and scene profiling).

The paper is organized as follows: Section 2 surveys related work into indoor localization area, Section 3 depicts the details of our solution, Section 4 provides both the description of the living lab hosting the EvAAL'13 competition, the binary sensor network on which leverages SALT, and the localization systems presented at EvAAL'13 that will be used to evaluate the proposed technique. Section 5 shows the performance of the proposed approach, while concluding remarks are presented in Section 6.

2 Related Work

In literature the indoor localization problem is solved by means of ad hoc solutions, among which one of the most promising is based on wearable technologies. Indoor localization systems can be classified based on the signal types and/or technologies (infrared, ultrasound, ultra wideband, RFID, packet radio), signal metrics (AOA angle of arrival, TOA time of arrival, TDOA time difference of arrival, and RSS received signal strength), and the metric processing methods (range-based and range free algorithms) [9]. Each solution has advantages and shortcomings, which, in most cases, can be summarized in a trade-off between several metrics (such as accuracy, installation complexity etc..). Data fusion techniques may be used to integrate the information obtained from different sensor sources [10–12] in order to reduce the localization error. In [10] the authors survey Bayesian filtering techniques for multi sensor fusion, arguing that probabilistic fusion methods are heavy in terms of computational load, requiring a centralized infrastructure to run the algorithms. A symbolic wireless localization device using a Bayesian network to infer the location of objects covered by IEEE 802.11 wireless network is developed in [13], where RSS received from different access points are quantified. Simple binary sensors in a Bayesian framework are also used in [14] to provide room-level location estimation and rudimentary activity recognition. In [15] a HMM (Hidden Markov Model) is used to stabilize a Bayesian-based location inference output in a WiFi-based localization system. In the domain of mobile robotics, RFID and Bayesian inference is used to perform obstacle detection, mitigating multipath effects [16,17]. A recursive Bayesian estimator, integrating WSN-based location data and kinematic information, is presented in [18]. Most of the works in literature employ Bayesian inference concepts in the design stage of the localization system and infrastructure.

Improvements in indoor positioning performance have the potential to create opportunities for businesses. However system performances greatly differ because both, the environments have a number of substantial dissimilarities and different technologies have a different performance. Our approach makes possible to improve the existing localization systems by adding a software overlay (that is sorce-agnostic) that receiving the information from the binary sensor network, usually deployed in smart environments, is able to reduce the overall localization error.

3 Source-Agnostic Localization Technique

The proposed solution aims both at providing a rough localization information in absence of a dedicated subsystem with a room-level accuracy, and at increasing the accuracy performance of an underlying localization system exploiting the context data provided by a home automation/monitoring sensor network typically deployed in a AAL smart environment. Several AAL projects [1] make use of this kind of sensor networks in order to help people in the automation of typical tasks [19] like switching on/off lights and HVAC systems [20] or to help remote caregivers in the activity monitoring of the assisted person [21]. Gathering the information about when and where a sensor or actuator is activated, we built a software overlay that can autonomously track the user movement in the house and, when a dedicated localization system is present, it can significantly enhance its accuracy.

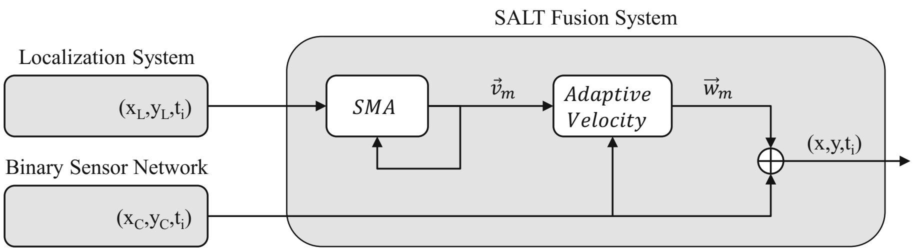

Fig. 1. The overall SALT fusion system

Figure 1 shows the overall SALT technique. For each sample provided by the localization subsystem (x_L, y_L, t_i) representing its output coordinates at time t_i, we built a geometric model of the trajectory that keeps track of the current position and of the velocity $\boldsymbol{v}_m$ calculated on previous samples received using a Simple Moving Average (SMA). When a context data (x_C, y_C, t_i) is received from the binary sensor network, the SALT overlay gives as output the coordinates of the corresponding activated sensor, since it represents a checkpoint of the user path. When no context data is received, we apply SALT on the data received from the localization system in order to fuse it with the information given by the binary sensor network in the previous steps.

[1] http://www.aal-europe.eu/

The basic assumption of the proposed fusing technique is that in the samples following the activation of a sensor, the position of the user is most likely in a neighbourhood of the position given by the previous contextual information. In order to take into account this *a priori* knowledge, when a new observation is received by the underlying localization system, we use the speed v_m to create a new vector $\boldsymbol{w}_m$ starting from the contextual data point and heading to the coordinates provided by the localization subsystem. The new estimated position (x, y, t) will be the head of $\boldsymbol{w}_m$ of size $w_m = v_m$. We iterate the process for each new context and localization data received adapting the parameter w_m to the new observations ($AdaptiveVelocity$ block in Figure 1). The following equations represent analytically the position update process:

$$x(t_i) = x(t_{i-1}) + w_m cos(\alpha)\Delta t$$
$$y(t_i) = y(t_{i-1}) + w_m sin(\alpha)\Delta t$$

where α represents the angle between $\boldsymbol{w}_m$ and the map reference system.

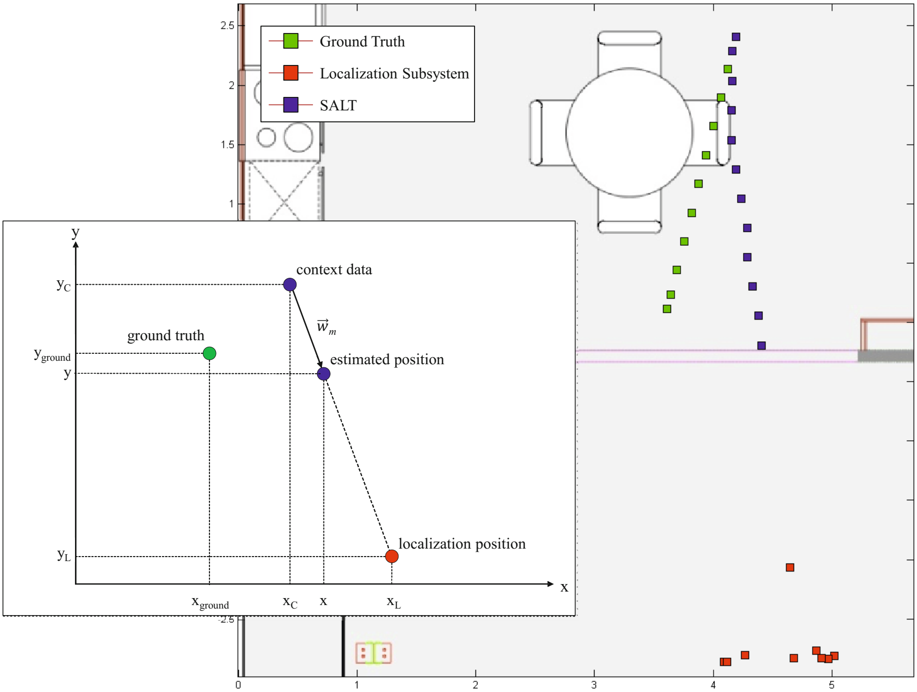

Fig. 2. Graphic representation of the SALT technique. In the box the coordinates of the actual position (ground truth), the context data, the localization system output, and the estimated position are shown.

Algorithm 1. Source-Agnostic Localization Technique

```
procedure Main
    (context_data, loc_data, salt) ← InitializeToNull()
    InitializeMap()
    while true do
        (context_data, loc_data) ← GetData()
        salt ← SaltFusion(context_data, loc_data)
    end while
end procedure

function SaltFusion(context_data, loc_data)
    if context_data ≠ null then
        salt.x ← context_data.x
        salt.y ← context_data.y
        salt.t ← context_data.t
    else if loc_data ≠ null then
        if salt = null then
            salt.x ← loc_data.x
            salt.y ← loc_data.y
            salt.t ← loc_data.t
        else
            vel ← ComputeVelocityComponents(loc_data, salt)
            salt.x ← salt.x + vel.x × (loc_data.t − salt.t)
            salt.y ← salt.y + vel.y × (loc_data.t − salt.t)
            salt.t ← loc_data.t
        end if
    end if
    return salt
end function

function ComputeVelocityComponents(loc_data, salt)
    avg_speed = SimpleMovingAverage(loc_data)
    vel.x ← avg_speed × cos(alpha(loc_data, salt))
    vel.y ← avg_speed × sin(alpha(loc_data, salt))
    return vel
end function
```

As shown in Algorithm 1, a first initialization phase is required in order to map the binary sensors to their actual coordinates. After this step, the algorithm waits for data from the pervasive environment and iteratively calls the core function *SaltFusion()*. Here we can see that when the proposed technique is used in absence of a dedicated localization subsystem (*loc_data* equals null), it is able to provide the position (structure *salt* in the algorithm) of the last context data (structure *context_data* in the algorithm) received. We can associate the information of the last room visited by the user using the coordinates of the corresponding sensor activated. This is useful in the case of AAL scenarios involving the use of assistive robots [5]. When an alarm is raised due to, e.g., a fall detection or emergency call, the caregiver can pilot the robot in the last known room occupied by the user for a prompt reaction.

Figure 2 shows a graphic representation of the update process after a context data is received. It shows a typical case where the underlying system gives a wrong position due to some changes in the environment like a door opened/closed or a furniture moved from its usual position. Indeed multipath effects due to reflections and diffraction from doors or furniture affect localization systems based on radio signal propagation [22]. Using the proposed technique these outliers are mitigated, increasing the overall accuracy of the underlying localization system fused with the proposed overlay.

4 Experimental Setup

In order to test and validate the proposed fusion overlay, we used the datasets provided by EvAAL [2], an international competition on localization systems for Ambient Assisted Living (AAL) scenarios. The objective of this competition is to award the best indoor localization system from the point of view of AAL applications [6]. EVAAL aims at enabling the comparison of different AAL solutions, by establishing suitable benchmarks and evaluation metrics that will be progressively refined and improved with time. In particular, EvAAL focuses not only on comparison of hard data such as accuracy of positioning and system reliability, but also on soft data like compatibility with existing standards, deployment effort and user acceptance.

4.1 The Living Lab

The competition was hosted by the Smart Home Living Lab, at the Technical University of Madrid[3] in Spain. The Living Lab is an open space environment of about 100 m^2 composed by a kitchen, a dining room, a bedroom, a bathroom, and a porch as shown in Figure 3. The Living Lab is equipped with domotic equipment, which includes configurable switches, lights, movement sensors, as well as electronic kitchen appliances. Hence the localization systems can exploit the information produced by these devices as consequence of the movements and actions of the actor. In the next subsection the description of the domestic equipment (i.e. binary sensor network) that we will leverage in this work will be given.

The fundamental studies of target tracking often focus on networks composed of sensor nodes with the most elementary sensing capabilities that provide just binary information about the target, indicating whether it is present or absent in the sensing range of a node. These so-called binary sensor networks constitute the simplest type of sensor networks that can be used for target tracking. In the

[2] http://evaal.aaloa.org

[3] http://smarthouse.lst.tfo.upm.es/

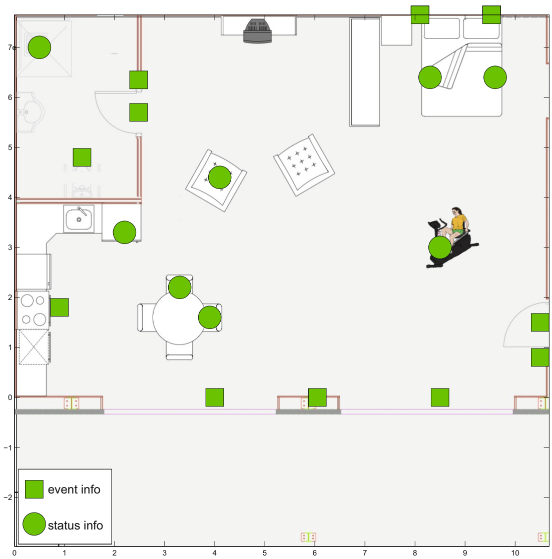

Fig. 3. The map of the Living Lab and the coordinates of the binary sensor network deployed in the Living Lab. Squares represent sensors giving information only when an event is raised, circles represent sensors giving information about their status.

Living Lab there are many simple binary sensors. These sensors have different properties which, when exploited, can reveal a surprising amount of information. Figure 3 shows the deployment of the binary sensors that the proposed source-agnostic localization technique exploits. The devices drawn with squares in Figure 3 are the following:

- Magnetic contact sensor: The Jung magnetic contact FUS4410WW are installed in the living lab. In particular, in the entrance door, in the living room door, in the bathroom door, and in the kitchen door.
- Switches: They are Jung KNX push-button modules F30, that generate the events when pressed.
- Liquid level sensor: This sensor has been used to understand when the user presses the button to drain the water closet. Indeed, it is able to detect the level of the liquid that flows.
- Electrical usage sensor: This sensor has been used to verify if the oven is turned on or not.

The binary information produced by these sensors are processed by the SALT system only when an event occurs i.e if the switches are pressed (on or off), or if the doors change their state (opened or closed). The devices drawn with circles in Figure 3 are the following:

- Electronic stationary bicycle with embedded computer and activity monitor: The output of this device is if the bicycle is running or not.

– Chair presence sensors: It is a force-sensing resistor that consists in a conductive polymer, which changes resistance in a predictable manner following application of force to its surface. This sensor has been used to verify if a user is in the chair or in the armchair.
– Bed presence sensors: The force-sensing resistor has been used to very the presence of a user on the bed.
– Flood sensor: This sensor has been used in the bathroom to verify if a user takes a shower.

In this case, the binary information is held by the SALT system until the status changes i.e when the user sits down on a chair the status is held until the user stands up.

4.2 Competitors and Technologies

In this section the competing localization systems chosen as test for the SALT technique are presented. In particular we selected the systems presented in 2013 edition since they are based on an heterogeneous technologies. Six teams were accepted to the 2013 indoor localization competition, the description of their systems is as follows:

AmbiTrack [23] – It is a marker-free camera-based localization and tracking system, i.e., it does not require the users to carry any tag with them in order to perform localization. This system also exploits the binary information coming from the switches and from the bicycle of the living lab.

LOCOSmotion [24] – This system is an indoor person tracking system that uses Wireless LAN fingerprinting and accelerometer-based dead-reckoning. Also this system exploits the binary information coming from the switches and from the bicycle of the living lab to infer the user position.

FEMTO-ST [25] – The systems is based on an hierarchical positioning algorithm which manages a multi-positioning system composed of a GPS positioning system, a Wi-Fi based fingerprinting and trilateration system, and a marker analysis system.

IPNLas [26] – The system uses an application for mobile phones (Android OS) that evaluating the RSS from the access points in the environment is able to localize the mobile pone inside buildings.

MagSys [27] – This system is based on the principle of resonant magnetic coupling, which means that it uses an oscillating magnetic field as the physical medium for localization. Thus, the mobile generate a magnetic field that periodically expands and contracts and the anchors evaluating this magnetic field. Furthermore the system includes additional acceleration and gyroscope sensors which are used as input to a filter stabilizing the location estimate.

RealTrack [28] – The mobile hand-held units periodically enter into active state and initiate the time-of-flight (ToF) ranging. Access points measure the RSS of the incoming radio signal. ToF and RSS data is processed by the server using a particle filter within localization algorithms. The structure of the building, air pressure value and the inertial measurement unit data are also taken into consideration by the system.

5 Performance Evaluation

In this section we first explain the tests made in the living lab followed by the performance analysis of the proposed technique applied to the systems competing in EvAAL 2013. During the tests, an actor wears the equipment the competitors

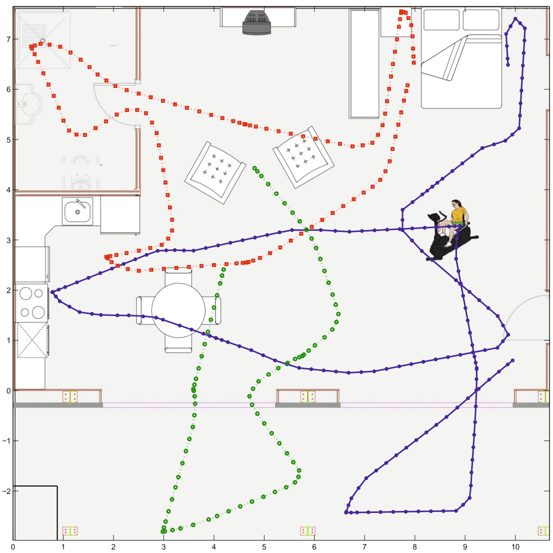

Fig. 4. The three different paths: path 1 (green line), path 2 (red line), and path 3 (blue line)

requires to carry (if any) and moves along a set of predefined paths (the chosen paths are represented in Figure 4). In this scenario, the actor has to be located while moving in the living lab along predefined paths. The expected output of the localization systems is the stream of his actual positions (in bi-dimensional coordinates) and the respective timestamps. During this phase, only the person to be localized is inside the Living Lab. Each localization system is requested to produce localization data with a frequency of 1 sample every half a second. The path includes 3 waiting points, where the actor has to stay still in the same position for 5 seconds. The reference localization system is used to compare the localization data generated by the competitors with the ground truth. The reference consists in a set of pre-defined paths the actor has to follow with a predefined speed. The Living Lab's floor was covered with marks (with different colors to distinguish the right and left foot) that indicate each single step the actor has to follow. Moreover, the actor was synchronized by a digital metronome that indicates the right cadence (one beep for each step), guaranteeing the repeatability of the test.

The performance of the proposed SALT system are given in terms of increase in *accuracy* of the competitors localization systems when the SALT overlay is

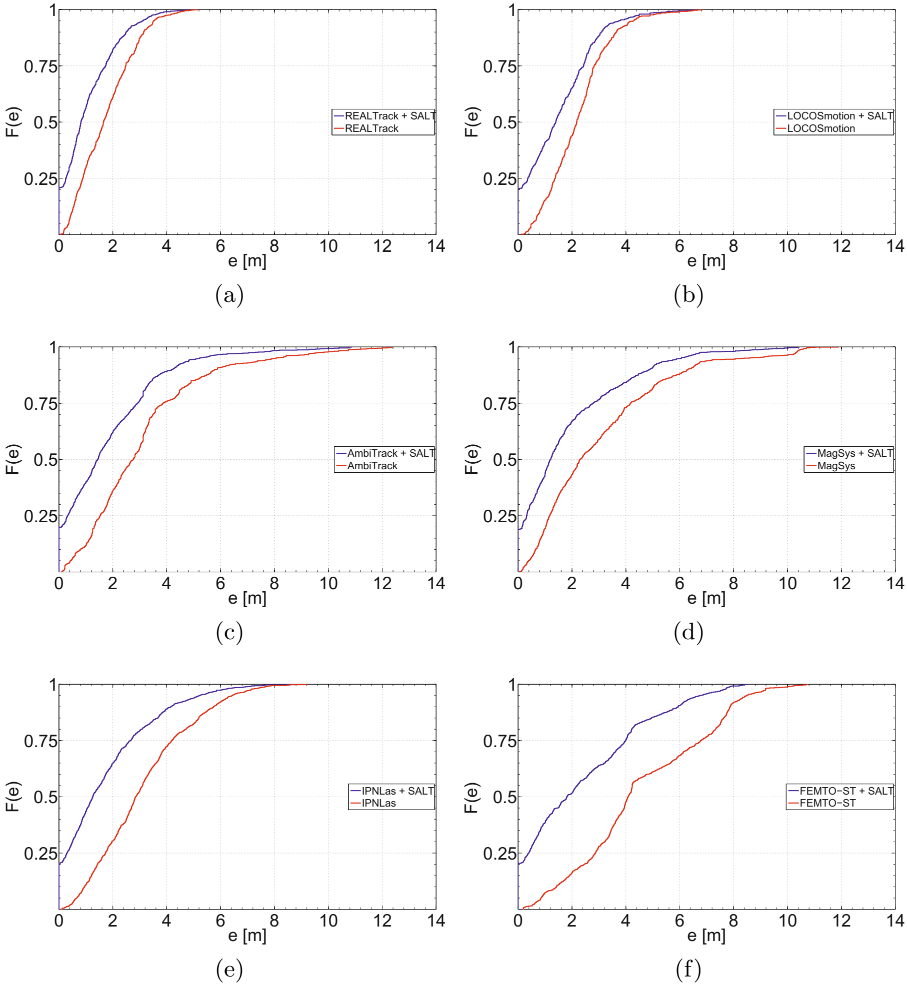

Fig. 5. CDFs comparison of the competitors localization systems error with and without the application of the SALT overlay

applied. The accuracy is the classical measurement for goodness of a localization system, it is based on samples of the distance between the point where the system thinks the user is and the point where the user really is. During the tests, the actor puts his feet on the marks at exactly the one-second times that are chimed by a loudspeaker: in those instants the reference point is the midpoint between the marks on which the feet are. The positions in intermediate instants are linearly interpolated from those points.

We define the error ϵ (equation 1) as the euclidean distance (in two dimensions) between the real point where the actor is (x_r, y_r) and the 2-D coordinates estimated by the competing system with or without the proposed SALT overlay (x, y).

$$\epsilon = \sqrt{(x_r - x)^2 + (y_r - y)^2} \quad (1)$$

The Cumulative Distribution Function (CDF) of ϵ is the probability that the localization error takes a value less than or equal to e meters and it is defined in equation 2.

$$F(e) = P(\epsilon \leq e) \quad (2)$$

Figure 5 shows the CDFs of the localization error ϵ using the EvAAL 2013 localization systems, with and without the proposed SALT overlay. Figure 5a shows the localization performance of the first place ranking of the competition, the REALTrack system, with and without the SALT overlay. The figure highlights that the accuracy increases by exploiting the proposed SALT technique: in 75% of the cases the localization error with the SALT overlay is lower than 1.7m compared with the 2.5m of error without the SALT overlay. The same trend can be seen for the other five competitors (subfigures from 5b to 5f). However, for two of the competitor, LOCOSmotion (Figure 5b) and AmbiTrack (Figure 5c), the increase in performance is not as evident as in other competitors. This because the two competitors already use the binary information coming from the switches and from the bicycle. In particular, these systems exploit the binary information to infer the user position at that time, but in the aftermath these information are not taken into account as in the case of the SALT system. From these results, we can conclude that the proposed SALT system significantly improves the accuracy of the localization systems.

Table 1. Accuracy comparison of the competitors localization systems without the application of the SALT overlay

	without SALT		
	1-Quantile	2-Quantile	3-Quantile
REALTrack	0.8840	1.6483	**2.4834**
LOCOSmotion	1.3728	2.1758	**2.8201**
AmbiTrack	1.5283	2.7590	**3.8603**
Magsys	1.1769	2.2986	**4.1779**
IPNLas	1.7295	2.8531	**4.1862**
FEMTO-ST / HMPS	2.8728	4.0774	**6.7843**

Tables 1 and 2 show in details the performance achieved by the localization systems we took into consideration compared with the application of the SALT overlay. The last column in 2 is the improvement when the third quartile is considered between using SALT or not. REALTrack, Magsys, IPNLas and

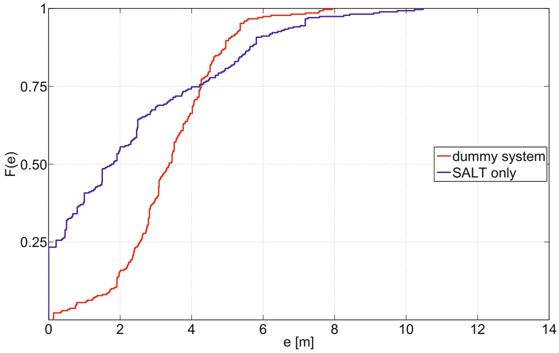

Fig. 6. The resulting CDFs for the SALT algorithm using only the binary sensor network and for the dummy localization system used as a comparison

FEMTO-ST systems improve their accuracy of about 30%, 33%, 36%, and 41%, respectively. While the systems that already used some binary information (i.e. LOCOSmotion and AmbiTrack) improve their accuracy of about 13% and 24% respectively. Moreover, from these results we can also conclude that, although the binary information reduces the localization error, the choice and the design of a localization algorithm is the most important issue. In fact, the ranking in terms of accuracy remains unchanged (see Table 2) except for the IPNLas and Magsys systems that, increasing the accuracy of about 36% and 33% respectively, would have had a better score.

Table 2. Accuracy comparison of the competitors localization systems with the application of the SALT overlay

	with SALT			
	1-Quantile	2-Quantile	3-Quantile	
REALTrack	0.2558	0.8162	**1.7322**	**+30.25%**
LOCOSmotion	0.3638	1.3957	**2.4318**	**+13.77%**
IPNLas	0.2976	1.2567	**2.6625**	**+36.40%**
Magsys	0.3212	1.2067	**2.7839**	**+33.37%**
AmbiTrack	0.3316	1.4387	**2.9170**	**+24.44%**
FEMTO-ST / HMPS	0.3885	1.8091	**3.9887**	**+41.21%**

Descrivere performance come stand alone system usando come confronto un dummy system che dice solo il centro della stanza In order to also show how the SALT overlay performs in absence of an underlying localization system, we run out algorithm on the three paths using only the sensors actually activated by the actor (a small subset of all the sensors available). We compared our results with a dummy localization algorithm able to give information on the room occupied by the actor during his paths: bathroom, main room, and porch. In Figure 6 the resulting CDFs of both system are represented showing a better outcome for SALT considering the first and second quartile. This is due to the intrinsic nature of the SALT system that gives a good estimation when the user is nearby the activated sensor. Considering the more realistic third quartile measure, the two systems performs almost the same (4 and 4.26 meters for SALT and the dummy system respectively) showing a good result for the proposed SALT technique since it doesn't need of a dedicated localization system exploiting the already present binary sensor network, typically installed in a smart house for AAL scenarios.

6 Conclusion and Future Work

In this paper we propose a Source-Agnostic Localization Technique (SALT) that fuses the information provided by a localization system already present a smart home with the information provided by the binary sensor network deployed in the environment. In order to evaluate and to show the full transparency of the proposed solution, we tested it by using the localization systems presented at the EvAAL 20013 international competition. On average, we measured an increasing of accuracy of about 30% from the performance experienced by the localization systems that don't use the context information, while the accuracy of the localization systems that exploit the information provided by the switches and by the bicycle in the living lab is, on average, about 20%.

In future work we plan to investigate how the performance changes according with the number of binary sensors deployed in the environment and the possibility to apply artificial intelligence techniques in order to deal with more than one user moving in the house.

Acknowledgments. This work was supported by the EU Commission in the framework of the GiraffPlus FP7 project (Contract no. 288173).

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http://www.springer.com/978-3-319-14111-4

Ambient Intelligence
European Conference, AmI 2014, Eindhoven, The Netherlands, November 11-13, 2014. Revised Selected Papers

Aarts, E.; de Ruyter, B.; Markopoulos, P.; van Loenen, E.; Wichert, R.; Schouten, B.; Terken, J.; Van Kranenburg, R.; Den Ouden, E.; O'Hare, G. (Eds.)

2014, XIII, 346 p. 144 illus., Softcover
ISBN: 978-3-319-14111-4