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CEO: A context event only indoor localization technique for AAL

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Abstract. Ambient Assisted Living applications are deployed in smart environments that provide some basic services, a typical example being user localization. AAL applications generally have low accuracy requirements for indoor localization; this opens the opportunity for parasitizing the existing smart environment infrastructure without adding dedicated positioning sensors.

In this scenario, one can exploit simple binary sensors that are usually present in the smart environment, such as light and appliance switches or intrusion detection sensors, to obtain a rough estimate of the position of the user. This application is device-free, meaning that the user is not required to carry any device in order to be localized.

In this paper we present CEO, a software-only system which we evaluate along the technical guidelines of the EvAAL competition. While the localization performance of CEO is lower with respect to most EvAAL competitors of past editions, it has the benefit of being non-intrusive, easy to install and perfectly compatible with other software systems: these characteristics would made it a potentially significant EvAAL competitor. While developing CEO, we only exploited the definition of the EvAAL competition environment as it was presented to competitors. The only inputs to CEO are the context events generated during the competition, which in 2012 and 2013 were limited to pressing light switches and using a stationary bicycle. We compare the performance of CEO against the results of those editions of EvAAL and show how it can be used to easily improve the performance of any EvAAL competitor.

Keywords: Indoor localization, Ambient Assisted Living, sensor data fusion

1. Introduction

The main goal of a smart environment is to provide services to its occupants, thanks to the use of a usually rich set of sensors and devices.

In this context, an Ambient Assisted Living (AAL) environment is one that is aimed at providing assistance with activities of daily living to the inhabitants, empowering them with the possibility of an independent life style despite minor disabilities. A typical scenario involves elderly people living alone at home [32]. AAL environments have gained increasing interest recently because of the growing number of elderly citizens in developed countries, and have been the object of significant funding in European research projects in the last several years, first under the AAL[1] umbrella and more recently under the European Innovation Partnership on Active and Healthy Ageing[2] (EIP-AHA) umbrella.

Any AAL system needs some method of locating the user, and indoor localization is an open research area which has produced much literature [40]. Generally speaking, an indoor localization system requires devices scattered through the environment for sensing the presence of people.

In this paper we analyze the possibility of exploiting the information provided by a basic domotic environment where light switches, anti intrusion systems and home appliances are able to communicate their activation over a home network, without any additional dedicated sensors or devices, in order to give an estimate of the position of a single inhabitant.

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[1] http://www.aal-europe.eu/
[2] http://ec.europa.eu/health/ageing/innovation/

The idea is to use a software-only method, so no additional hardware is needed besides the devices that are already installed in the domotic environment; the software reads the events generated on the home network and implements a trivial movement model. Possible ways of improving the system, alone or in conjunction with other sources of position information, are suggested.

While many research projects have targeted sensor-rich real AAL environments [2,34,42], we are aware of none that openly provides sensor event traces coupled with an accurate ground truth of the movements of the inhabitants. Conversely, researchers that have focused on logging precise traces of people movements in indoor movements (typically using cameras) [8,9,13] have not concentrated on real AAL environments and thus we are not aware of available data sets of indoor positioning data that include extensive event traces from sensors triggered by residents in their activities of daily living. In this context, as a way to test and evaluate our proposed concept in a controllable and realistic way, we make reference to the EvAAL[3] framework. EvAAL is a yearly competition [6] aimed at defining benchmarks for the evaluation of AAL systems. It was born in 2011 as an offspring of the universAAL FP7 project, financed by the European Union [16] for creating a FLOSS software platform for AAL systems. EvAAL is a project hosted by the AALOA[4] open association, which is devoted to:

> *Bring together the resources, tools and people involved in AAL in a single forum that makes it much easier to reach conclusions on provisions needed to achieve AAL progress [12].*

Defining comprehensive benchmarks for AAL systems is a daunting task, and during its first three editions, EvAAL has concentrated on evaluating AAL subsystems, with the long-term goal of gradually expanding the evaluation procedure to groups of subsystems and, eventually, to complete AAL systems.

There have been two subsystems considered so far in EvAAL, specifically: localization of single persons in a domestic environment and low-level activity recognition. To be consistent with the mission of the competition, the evaluation procedures defined for both has kept into account several criteria, some of which relative to the performance of the subsystems, others relative to how well the competing systems could integrate within an AAL environment. All in all the final score awarded to a competing system is composed by summing five different scores, of which the one relative to *accuracy* accounts for 35% of the total, while the others relate to *reliability* or *delay of the measures*, *installation complexity*, *user acceptance* and *interoperability* with AAL systems. The purpose of considering so many different criteria is to set a balance among the quality of the main output of the system, that is the accuracy, and all the other qualities that make the localization or activity recognition subsystem a "good citizen" of a complex AAL system. A brief discussion on how this balance is achieved is done below, here it suffices to say that we believe that the balance is well chosen, and we build our work on this assumption.

In this paper we concentrate on the localization competition as defined by the EvAAL rules set for the 2012 and 2013 editions. In those editions, the competitors were provided with some simple context information, namely events corresponding to light switches activations and the use of a stationary bicycle. These events were meant to ease the work of the competing localization systems and increase their accuracy. However, few of the competitors have used that information, probably because doing so would have required changes to their systems that were deemed too expensive. This observation leads to some questions: is that simple context information really useful? how much would a competing system be advantaged by using it rather than ignoring it? and, more radically: is it possible to build a viable localization system that only uses that context information, and how well would it perform in comparison to the other competing systems? This paper is meant to answer these questions. The source code of the proposed algorithm is available in [38] together with the used datasets.

In the literature the concept of using context information in an AAL system is well established. Two examples are [4], where motion sensors and appliance switches are used to monitor the patterns of activity of a person at home and [43], where light and appliance switches and bed and chair usage sensors are used to detect abnormal behavior of a person at home. We believe that the importance of using context information from already-installed devices is bound to keep growing. Specifically, information parasitically obtained from light switches, appliance switches and intrusion detection switches can be very precious in any smart home environment and a good starting point for localizing the user at home.

[3] http://evaal.aaloa.org/
[4] http://www.aaloa.org/

We think that investigating the above questions is in fact significant to further the state of the art in indoor localization meant for AAL systems, that is with a required accuracy not smaller than a person's body footprint and not bigger than the size of a room. One important reason is that we think that real-life systems will necessarily gather input from different sources and fuse them to obtain the location estimate. In fact, many of the most successful systems that competed in EvAAL have used some sort of data fusion from different sources. Data fusion is particularly appealing because it is robust with respect to varying availability and quality of data sources, and can take advantage of low-quality data, such as the context information provided during the EvAAL competition. The winner of the localization track in 2013 has been RealTrac, a system that relies heavily on data fusion using a particle filter [29]. Data fusion applied to indoor localization for AAL is recently receiving more and more attention [1,17,31].

Next sections provide a literature analysis of existing indoor localization systems outside and inside AAL in Section 2; an overview of the characteristics and the performance of EvAAL competitors in 2012 and 2013 is given in Section 3; a description of CEO, the simple program we used to obtain a location estimate based only on context information (light switches activation and stationary bicycle usage) is provided in Section 4; and finally, in Section 5, a summary of the performance of CEO with respect to competitors and an evaluation of the improvements that a simple fusion algorithm would have brought to the results of EvAAL competitors. The conclusions contain a discussion on the usefulness of the information gathered through this analysis and directions for future work.

2. Related work

Many researchers have faced the challenge of indoor localization by proposing systems based on ad hoc solutions [15,20,25]. These indoor localization systems can be classified based on the signal types and technologies used (infrared, ultrasound, ultra wideband, radio frequency identification, packet radio), signal metrics (angle of arrival AoA, time of arrival ToA, time difference of arrival TDoA, and received signal strength RSS), and the metric processing methods (range-based and range-free algorithms).

Among the most successful commercial and research systems we find: Active Badge [45] that uses infrared sensors, Active Bat [18] that uses ultrasonic sensors, Easy Living [24] based on vision sensors, MotionStar [39] that uses a dc magnetic tracker, RADAR [3] that uses a wireless local area network, SmartFloor [33] based on pressure sensors to measure proximity to a known set of points, WhereNet[5] that employs radio frequency identification technology, and other research projects based on inertial methods [50,51] and passive infrared sensors [22,26] to localize and trace the resident.

Each solution has advantages and shortcomings, which in most cases can be summarized as a trade-off between several metrics, such as accuracy, user acceptance, installation complexity, and cost. When we consider the Ambient Assisted Living scenario, the user acceptance becomes critically important. Many AAL scenarios require continuous monitoring of the user position, e.g. in emergency situations like falls, in assisting the elderly in house navigation and mobility tasks, or in the long term monitoring of user rooms occupancy to control his mobility behavior. In these cases the localization system must be easily accepted by the user and, possibly, requiring few or no worn devices [23].

In device-free localization systems people do not need to carry devices or tags. This is important, as people are generally unwilling to wear extra devices, especially at home [48], or they can forget to put the device on. Furthermore, mobile positioning devices use batteries and require regular monitoring and changing. Some device-free localization systems use cameras [19,24], but they raise privacy concerns as most people are unwilling to install any system that they perceive as intrusive in their homes [21,44].

The main technologies that can be used in device-free localization are based on pressure sensors [28], sound source localization [27], ultrasound [30], and radio frequency (RF) [7,41,46]. The main drawback of these methods is the large number of devices that must be deployed in the environment, their deployment, and their cost that is usually high.

A solution to this problem is using infrastructure-mediated sensing techniques which exploit existing devices in a building for positioning purpose. They include air conditioning channels [35], electrical wires and switches [36], and water pipes and plumbing [14]. This is the approach adopted by CEO, which has the advantage of not requiring the installation of new sensing infrastructure in a home. Hence, it is easy to in-

[5] http://www.wherenet.com/

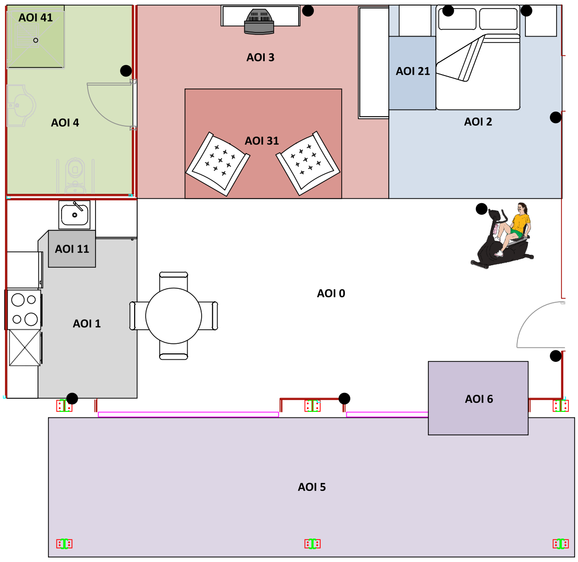


Fig. 1. Map of the UPM living lab, including the location of switches (black dots) and the stationary bicycle. The rectangles represent the areas of interest (`AoI N`).

stall and maintain since it is based on a software-only component exploiting usually inexpensive and aesthetically pleasing devices already deployed in the house. On the other hand, the accuracy of the proposed localization technique, like all this kind of systems, is low compared to other ad hoc positioning systems outside the AAL scenario.

3. The EvAAL competitions in 2012 and 2013

In the 2012 and 2013 editions, the EvAAL track dedicated to localization was held at the living lab facilities of Universidad Politécnica de Madrid (UPM), in Madrid, Spain. The setting and the rules were the same, but the specific paths walked by the actor were different in the two editions. However, the paths were set using the same criteria, so we believe that the results obtained by the competitors in these two editions are comparable.

3.1. Localization competition setting

Figure 1 is the map of the setting of the localization competition. The area is composed of an indoor open space, a bathroom and an outdoor patio. The bathroom is corresponding to the green rectangle marked `AoI 4`, the patio to the purple rectangle marked `AoI 5`. Kitchen furniture including a stove and a fridge is on the left side, a stationary bicycle is depicted on the right. The main entrance is the door depicted on the right. Two wide sliding doors connect the indoor space to the patio. Some furniture is present: a dining table with four chairs, two armchairs in front of a TV set on a small table, a double bed and two bedside tables.

The colored rectangles marked with `AoI N` are *Areas of Interest*, used for computing the accuracy score as detailed below.

Light switches in the living lab are instrumented and connected to the living lab network; when a switch is pressed, it generates an event (message) that is made available to the competing systems through the connection they use for sending their real-time location estimates. The position of a switch is shown as a circle in Fig. 5. The stationary bicycle generates an event when it is being used.

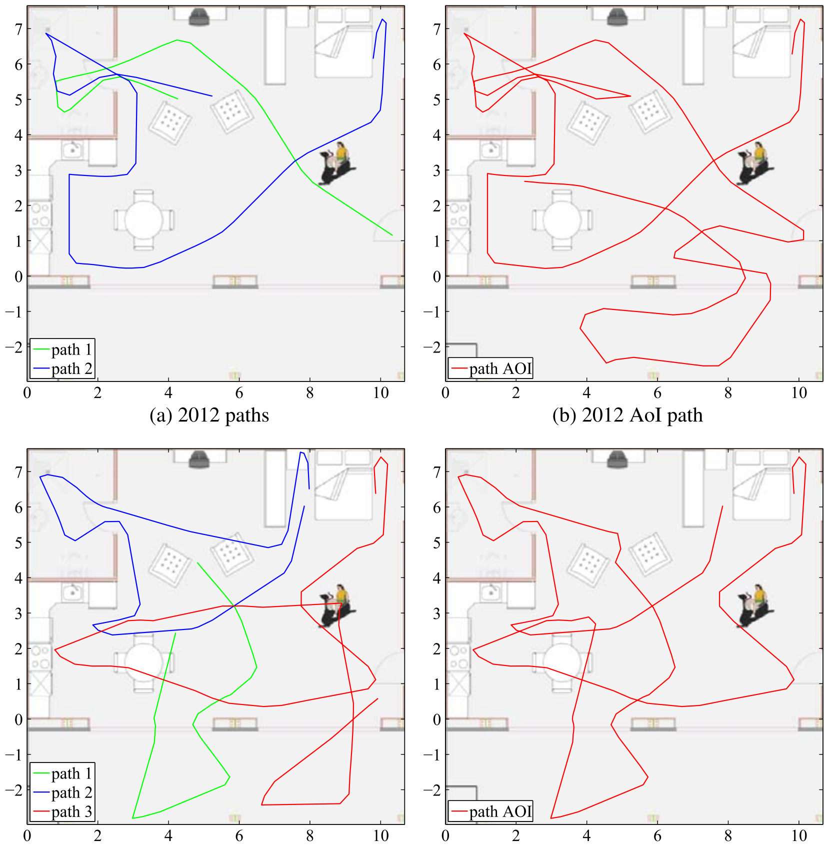
3.2. Paths and AoIs

The EvAAL competition computes accuracy in two different scenarios. The first one is based on *paths*, which are predefined routes marked on the floor of the living lab, which are walked by an actor at a given step rate, marked by a chime. For this scenario, the distance between the actor's position and the estimated position is evaluated, as detailed below. The second scenario is based on *areas of interest* (AoI), which are predefined rectangles marked on the living lab's area. For this scenario, the evaluation consists in verifying that the estimated AoI is the one where the actor is. In this paper we only consider the path scenario, for simplicity and consistency of comparison. Paths and AoIs are depicted in Fig. 2.

3.3. Scoring criteria

Scoring is based on different criteria, which are detailed on the EvAAL technical annex for the localization competition [5]. The final score is the sum of five parts, illustrated in Table 1.

Accuracy and *availability* are *hard measures*, that is numbers obtained from an objective procedure, and are both relative to the real-time output of the competitor system. Accuracy describes how well the location estimate approximates the real position [6], while availability depends on how regularly the system generates real-time position estimates at the required rate of two per second. Both measures only depend on the samples



(a) 2012 paths (b) 2012 AoI path

(c) 2013 paths (d) 2013 AoI path

Fig. 2. The 2012 and 2013 paths and AoIs.

Table 1

Scoring criteria for the 2013 localization competition

Criterion	Quote	Type
Accuracy	0.35	hard, automated
Availability	0.20	hard, automated
Installation complexity	0.10	hard, manual
User acceptance	0.20	soft, interview
Interoperability with AAL systems	0.15	soft, interview

sent by the competing system and can be measured in an automated way.

The accuracy score is the average between two values: the AoI score and the paths score. The AoI score is the ratio of correct AoI estimates to the total AoI estimates, where an estimate is N-valued and indicates either one of the AoIs or "outside of any AoI".

In order to define the paths score, we define the *error* as the Euclidean distance between the position of the actor and the (x, y) estimate given by the competing system. For each estimate given by the competing system, the error is computed and the third quartile of the errors is considered. The rationale for the choice of the third quartile is described in [6].

To the third quartile of the error T the following function is applied:

$$\text{score} = \begin{cases} 0 & \text{if } T > 4 \text{ m} \\ 10 & \text{if } T \leqslant 0.5 \text{ m} \\ 4 * (0.5 - T) + 10 & \text{if } 0.5 < T \leqslant 2 \text{ m} \\ 2 * (4 - T) & \text{if } 2 < T \leqslant 4 \text{ m} \end{cases}$$

The above function is depicted in Fig. 3. As described in [6], the flat maximum ensures that the score is not impaired by inaccuracies smaller than 50 cm; the long tail up to 4 m is intended to discriminate among competing systems that give a completely wrong or random output and those that, while inaccurate, are able to give an idea of the area where the actor is.

Installation complexity is still a hard measure, but needs human intervention, as it is based on the number of people who perform the system installation and

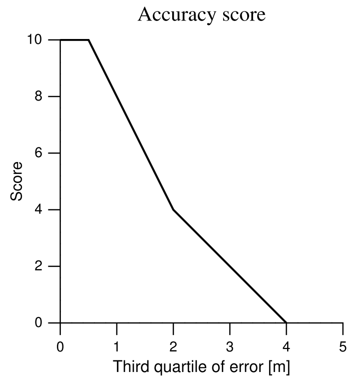


Fig. 3. Accuracy score as function of the third quartile of error.

the length of time needed to complete the installation.

User acceptance and *interoperability with AAL systems* are soft measures: they are both based on answers given to a predefined interview. While the interviews are designed to allow as an objective an answer as possible, there is still some room for expert judgment on the part of the interviewing pool.

The balance between the weights of these measures is given in Table 1. It reflects the relative importance of various factors to be considered when evaluating a localization system to be included in a generally complex AAL environment [6].

We think that the balance adopted by the EvAAL competition is basically correct, and consequently it makes sense to think about a system that is built to maximize the EvAAL's score as shown in Table 1. Our basic idea is that a software-only system has the potential of obtaining a high score, provided it is written with attention to standards and is distributed as free software [37], because such system would be able to easily obtain the maximum score in all criteria from the second one on.

In fact, real localization systems may have a problem with *availability* because of their real-time nature and the difficulty of managing several sources of continuous data and possibly complex computations while communicating with the base system, usually in wireless mode. Examples are systems that use data fusion based on particle filtering, which is particularly computing intensive, or those reading data streams from cameras, which generate a lot of data. Also wireless communication can cause problems, one specific case was LOCOSmotion, which had a perfect *availability* score in 2012 yet, due to a problem with wireless communications in an Android library, got a low score in 2013. In every case mentioned, tuning the system can solve the issue. Anyway, all these issues are nonexistent as far as CEO is concerned: computation is very simple, to the point of being insignificant; input data are reduced to a minimum, as only context events from user interaction with the environment are considered; and communication need not be wireless, and does not even require a network, as CEO can run side-by-side with the system that consumes the real-time location estimates.

CEO does not require any *installation*, as it needs no hardware devices other than those that are already present in the environment. On the other side, every localization system that is not purely software requires some sort of installation, and the time required is the base for the *installation complexity* score.

The *user acceptance* score is based on how well the system integrates with the furniture, how annoying is to wear it and how much maintenance it requires, but nothing of this is relevant for CEO: the first two are not an issue for software, and maintenance is not to be considered because CEO can run on the same hardware as the system that consumes the real-time location estimates.

Finally, the *interoperability with AAL systems* score is based on criteria such as standards conformance, availability of documentation and licensing of source code, all of which are completely satisfied by the present paper.

The only remaining problem is the first and foremost scoring criterion: *accuracy*.

So the question is: is it possible to exploit the little context information given by the EvAAL environment to obtain a non-negligible *accuracy* score? It is not easy to give a significant answer in a general fashion, but the environment we decided to consider gives us a reference not only for the scoring criteria, but also for the evaluation. In the rest of the paper, we are going to use the scoring criteria used by EvAAL for the accuracy, the paths used in the 2012 and 2013 editions and the results of the competitors of those editions for a comparison.

3.4. Competitors

A total of 14 competitors have participated to the localization track of EvAAL in 2012 and 2013. They are listed in Table 2.

Most competing systems use some sort of radio frequency (RF) measurement as the base data. Of the fourteen competing systems, only four do not use radio

Table 2
Competitors of the 2012 and 2013 localization track

Year	Competitor	Accuracy score	Total score	Method	Device free	Fusion	Using context info
2012	CAR	7.57	7.70	RFID trilateration and PDR	no	x	–
2012	CPS Group @ Utah	6.98	7.45	ZigBee radio tomography	yes	–	–
2012	iLocPlus	3.64	4.86	ultrasound trilateration	no	–	–
2012	LOCOSmotion	0.64	5.23	WiFi RSS FP and PDR	no	x	–
2012	OwlPS	0.78	6.29	WiFi RSS FP and trilateration	no	–	–
2012	Smart-Condo	2.81	5.41	PIR and tracking	yes	–	x
2012	TAIS	0.67	4.22	ZigBee RSS FP	no	–	–
2013	AALocation	4.20	2.15	ZigBee RSS with sector antennas and PIR	no	x	–
2013	AmbiTrack	2.46	6.18	3D videocamera processing	yes	–	–
2013	IPNlas	1.12	6.18	WiFi RSS FP with Kalman filter	no	–	–
2013	LOCOSmotion	3.47	6.02	WiFi RSS FP and PDR	no	x	x
2013	Magsys	1.55	5.66	resonant magnetic fields	no	–	–
2013	RealTrac	4.14	7.21	UWB ToF and RSS ranging, PDR	no	x	–
2013	SHMPS	0.52	5.25	WiFi RSS FP, trilateration and marker detection	no	x	–

Abbreviations: FP → fingerprinting, PIR → presence infrared sensors, PDR → pedestrian dead reckoning, RF → radio frequency, RFID → RFID tags, RSS → received signal strength, UWB → ultra wide band

waves as a measurement system, but use instead presence infrared sensors (PIR), videocameras, ultrasound, resonant magnetic fields. Of these four, two are in the top 50% of accuracy score results, thus giving no indication as to whether the more popular RF technology should be seen as more successful.

Two systems in 2012 and four systems in 2013 use some sort of data fusion, i.e. they have internal methods for making good use of localization data coming from different sources. Of the four systems (two in 2012 and two in 2013) having reasonably good accuracy performance, that is, an accuracy score higher than 4, three have used some sort of data fusion.

Systems using data fusion have most of the logic in place for exploiting the switches and static bicycle events generated by the living lab infrastructure. And yet, only one system in 2012 and one system in 2013 exploited that context data.[6] The systems that used the context info did not fare particularly well, but neither had too bad an accuracy score: the values were 2.81 and 3.47.

But it is interesting to notice that, both in 2012 and in 2013, systems in the first three places not necessarily had a good accuracy score. In both years, the third overall place was held by systems having an embarrassingly low accuracy score, with values of 0.78 and 1.12.

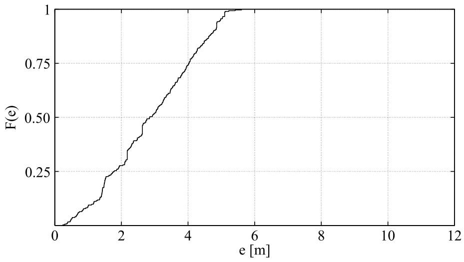
Two lessons here: first, while we believe that overall the scoring method of EvAAL is "good", systems with bad localization performance can obtain high overall scores, which means that a software-only system that relies only on context information may have some hope of getting a good placement, because it will obtain the maximum score in all metrics but accuracy.

Second, systems using the context information had not-so-bad accuracy performance, which is a hint that the other systems may have benefited from using context information as well. If, as we believe, future practical systems are going to rely more and more heavily on fusion of possibly low-quality data coming from diverse sources, context information provided by light switches can be effortlessly integrated.

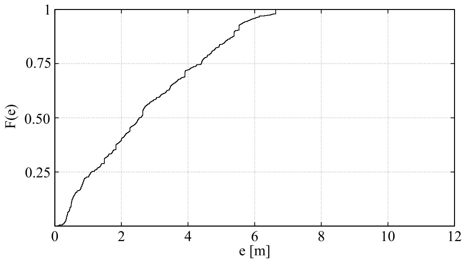
4. The CEO localization technique

We are now describing a very simple method for obtaining a position estimate from context data only, using the little information that was provided to competitors of the 2012 and 2013 EvAAL competitions. The method is thought to be as simple as possible, so no knowledge of the map is introduced, apart from the perimeter (a rectangle in EvAAL's case). We call it CEO, for "context event only".

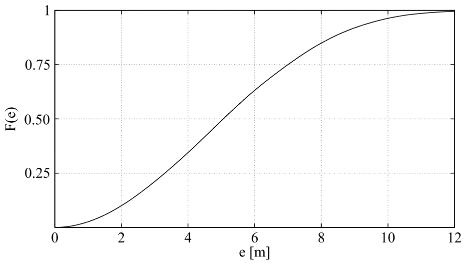
[6] AmbiTrack implemented a fusion algorithm which accounted for context info, but the implementation was faulty and could not be used during the competition.



(a) Cumulative function distribution for CEO, EvAAL 2012.



(b) Cumulative function distribution for CEO, EvAAL 2013.



(c) Cumulative distribution for a random position estimator (uniform distribution of estimates over the entire area.

Fig. 4. Comparing CEO with a "blind" system.

We start by dividing the competition area into *Voronoi cells*, where the *seeds* of the tessellation are the event generators, that is the light switches and the static bicycle, as shown in Fig. 5. When an event is produced by a given generator, the estimated position is set to that generator. It remains to be decided how to deal with what happens before any event is generated and after each event is generated, keeping in mind that the algorithm should work in real time, so it needs to be causal (no future knowledge of events).

As far as the starting point is concerned, we consider the centroids of the Voronoi cells, which are marked with red squares in Fig. 5. Then we consider the centroid of the convex hull of the cell centroids, which is marked with a black diamond in Fig. 5; we call *centre* this point. The *centre* is the starting point, that is the estimated position when no event has been received yet.

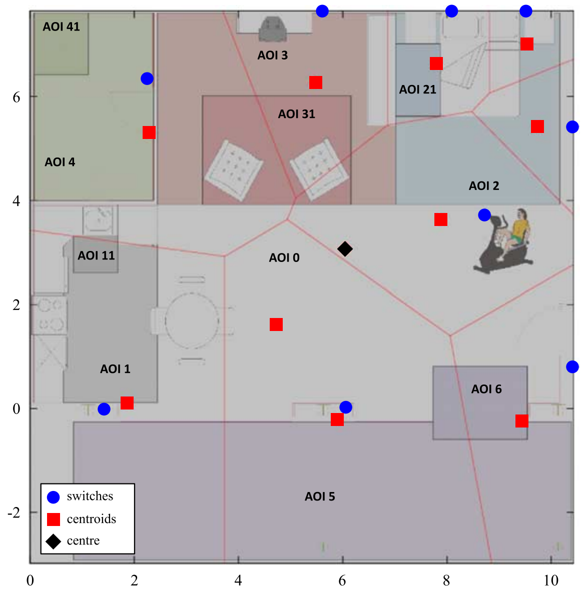


Fig. 5. Position of switches are marked with blue circles, Voronoi cells relative each to an event generator (a switch or the static bicycle) are marked with thin red lines and their centroids with squares. The black diamond represents the centroid of the convex hull of the cell centroids (Color figure online).

When an event is received, the estimation is set to the event generator position; from then on, it moves linearly so that it gets to the event cell centroid in 7.5 s; from then on, it moves linearly so that it gets to the *centre* in 7.5 s more. From that moment on, it stands still. The estimate jumps immediately to the event generator position as soon as a further event is received.

Figure 6 shows the finite state machine (FSM) describing the steps performed by the CEO algorithm. Each state, called $\boldsymbol{v_0}$, $\boldsymbol{v_1^i}$, and $\boldsymbol{v_2^i}$, represents the velocities at which the estimate changes its position on the map. Specifically, $\boldsymbol{v_0}$ has a null speed and it is used to indicate that the estimate is still on the *centre* position. This is the initial state that is kept if no event is received ($\bar{e}_i$) during the time t. When an event is received (e_i), the estimate is set to the event generator position and t is set to zero. In this case, the FSM goes into the state $\boldsymbol{v_1^i}$ where the velocity is directed from the event generator position to the centroid c_i of the relative Voronoi cell and has speed:

$$v_1^i = \frac{|position(e_i) - position(c_i)|}{\tau_1} \tag{1}$$

where τ_1 is set to 7.5 s. In this state the estimate moves towards the cell's centroid c_i with speed v_1^i until $t \leqslant \tau_1$ or a new event is received. In the latter case, the FSM

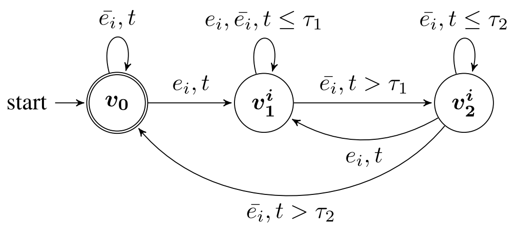


Fig. 6. The finite state machine representing CEO.

remains in the current state, but the estimate is moved to the new event generator position and t is reset to zero. If on the other hand no event is received and $t > \tau_1$, the FSM changes its state to $\boldsymbol{v_2^i}$, indicating that the estimate will move from c_i to the *centre* position with speed:

$$v_2^i = \frac{|position(c_i) - position(centre)|}{\tau_2 - \tau_1} \tag{2}$$

where τ_2 is set to 15 s. The FSM remains in this state until $t \leqslant \tau_2$, when it returns to the initial state $\boldsymbol{v_0}$, or until a new event is received, in which case it returns to the state $\boldsymbol{v_1^i}$.

This almost trivial algorithm can be easily extended and improved, first of all by adding some knowledge of the map, such as the positions of doors, internal walls and furniture. Additionally, instead of using simple Voronoi cells, supervised algorithms where one can draw the cells by hand or semi-supervised algorithms based on meta-information and artificial intelligence can be used, trying to guess what are the places where someone would typically go after pressing a light switch. Some memory of the past history of switching sequences may be retained, so that it can be used to forecast future movements of the actor. All these improvements would only need additional software, and would not consequently change the nature of the proposed method.

4.1. *Accuracy performance of* CEO

The performance of CEO in terms of accuracy that is illustrated here cannot be directly compared with the performance of systems in Table 2, because it would unduly advantage CEO. In fact, we only consider scenarios without a "disturber", that is a second actor moving in the same scenario as the first one and generating switch events in addition to the actor to be localized. The reason is that CEO is simply not sophisticated enough to give significant results in such situations. The exclusion of the paths including a "disturber" allows a comparison on an equal basis, which is the object of the next section.

Figures 4a and 4b illustrate the performance in the 2012 and 2013 scenarios, as far as the error distribution is concerned, that is, not accounting for the AoI paths. As expected, the results are not particularly appealing, with a median error of 2.5 M and 2.8 m in the two years, and a third quartile of 4.4 m and 4.0 m respectively. These numbers are significantly better than those that would be obtained by a "blind" system, one which generates a random estimate with uniform distribution over the whole map, shown in Fig. 4c. This is all that is needed to tell that CEO is able to add information to an existing localization system by means of data fusion, or even to provide a really cheap and non-intrusive low-quality estimate in the absence of other information.

In the next section we see how much this information is significant with respect to the systems competing in EvAAL.

5. Results

At the end of the Section 3 we mentioned about two lessons learned. We are going to verify that they are indeed valid.

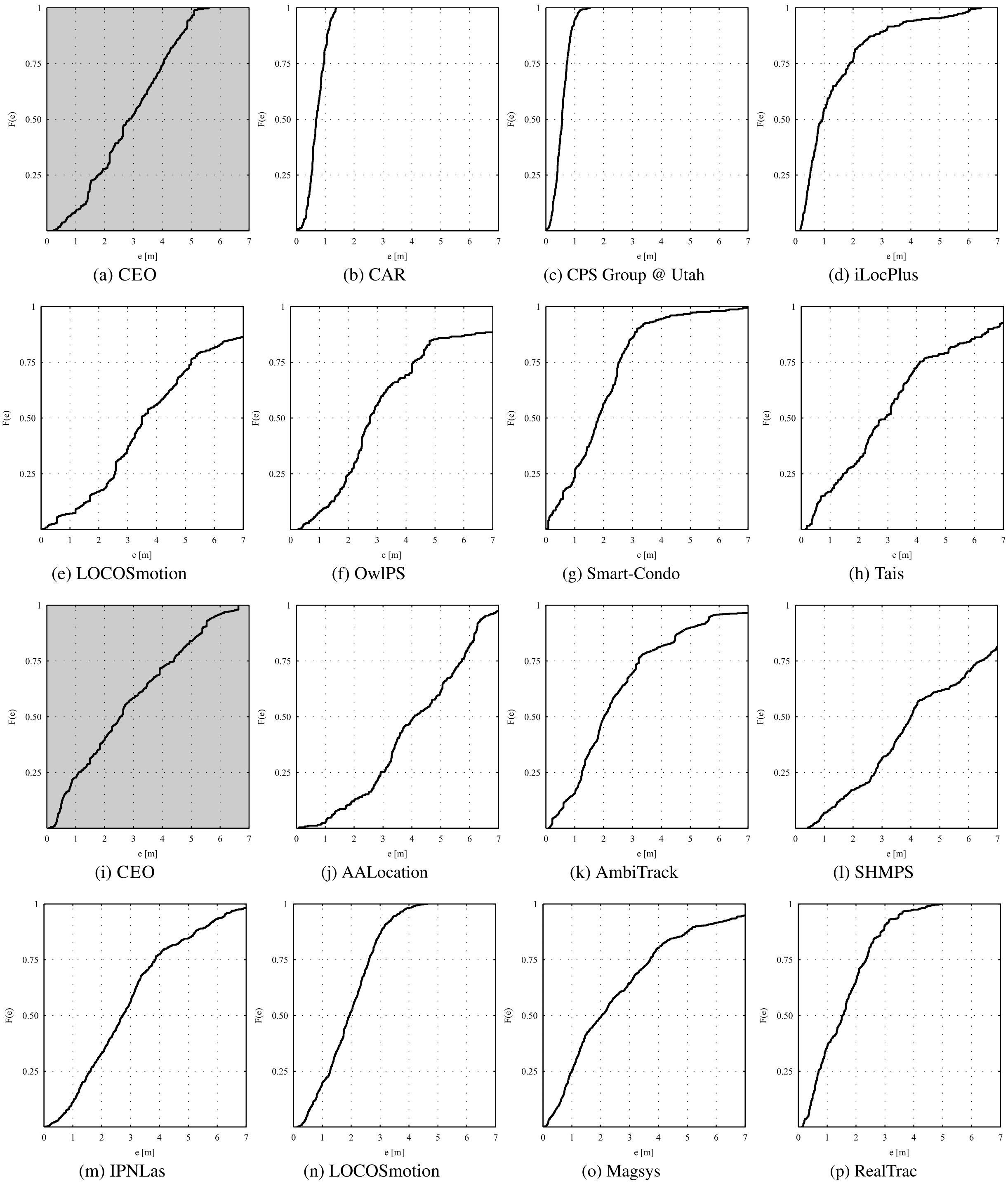
First, we verify that the performance of CEO is comparable to those of the competitors. Second, we verify that a trivial fusion of CEO's output with the competitor's output brings an improvement at very little cost.

It is important to note that all the comparisons made in the section are made only on the EvAAL paths not including a "disturber", as already mentioned.

5.1. *Direct comparison of* CEO *with competing systems*

Figure 7 provides a direct comparison among all the cumulative function distributions (CDF) of errors for all the competitors in 2012 and 2013, together with the same results from CEO. The results from CEO are the same as those shown in Fig. 4, where they are compared with a "blind" system.

We observe that CEO is definitely not the worst system. This is true in 2012 and even more in 2013, when the overall quality of the competing systems was lower, as far as only the accuracy scoring is considered. Remembering that the EvAAL score is composed



(a) CEO (b) CAR (c) CPS Group @ Utah (d) iLocPlus

(e) LOCOSmotion (f) OwlPS (g) Smart-Condo (h) Tais

(i) CEO (j) AALocation (k) AmbiTrack (l) SHMPS

(m) IPNLas (n) LOCOSmotion (o) Magsys (p) RealTrac

Fig. 7. CDFs comparison of systems accuracy in EvAAL editions 2012 and 2013.

for 65% by the criteria mentioned in Section 3.3, all of which would be at the maximum for CEO, we see that CEO would have mounted the podium both in the 2012 and 2013 editions, in both cases without "cheating", that is, while obtaining a respectable accuracy performance.

```
function fused_estimate (competitor_estimate, CEO_estimate, tau)
    reliability = exp(-tau/decay)
    radius = maxradius * (1 - reliability)
    if (Euclid_dist(competitor_estimate, CEO_estimate)) < radius)
        return competitor_estimate
    else
        return CEO_estimate
```

Fig. 8. Algorithm for fusing CEO results with another system's results.

5.2. *Improving the competing systems through* CEO

Here we try to improve the performance of the competing systems by adopting a simple fusion mechanism with CEO. In a real implementation, localization systems that already include some sort of fusion should probably use that to include data provided by CEO.

The fusion method we adopted consists in defining a circle around CEO's estimate, whose radius depends on the *reliability* of the estimate, which we set at 1 as soon as the context event is produced and then decays with time. The *radius* of the circle is null at maximum reliability and increases with decreasing reliability. If the competing system's estimate falls outside of the circle, it is simply substituted by CEO's estimate. This unsophisticated method may in principle worsen the overall performance, especially when the competing system has good performance right from the start. In practice, the application of this method almost always produces an improvement.

The way the radius of the circle grows is defined as follows. Every time a context event is received by the system, an exponentially decaying function representing *reliability* is started:

$$reliability = \exp\left(-\frac{\tau}{decay}\right) \tag{3}$$

where *decay* is set to 10 seconds and τ is the time elapsed from the last event. The radius is then computed as

$$radius = maxradius(1 - reliability) \tag{4}$$

where *maxradius* is set to 10 meters. Note that *maxradius* is the size of the location setting, and that *maxradius* / *decay* is about the maximum speed one can expect in an AAL environment. The box in Fig. 8 illustrates pseudo-code that produces a fused estimate starting from a competing system's estimate and the CEO estimate.

Figures 9 and 10 depict the cumulative distribution functions of errors for all competing systems before (red thick line) and after (blue thin line) application of fusion with CEO.

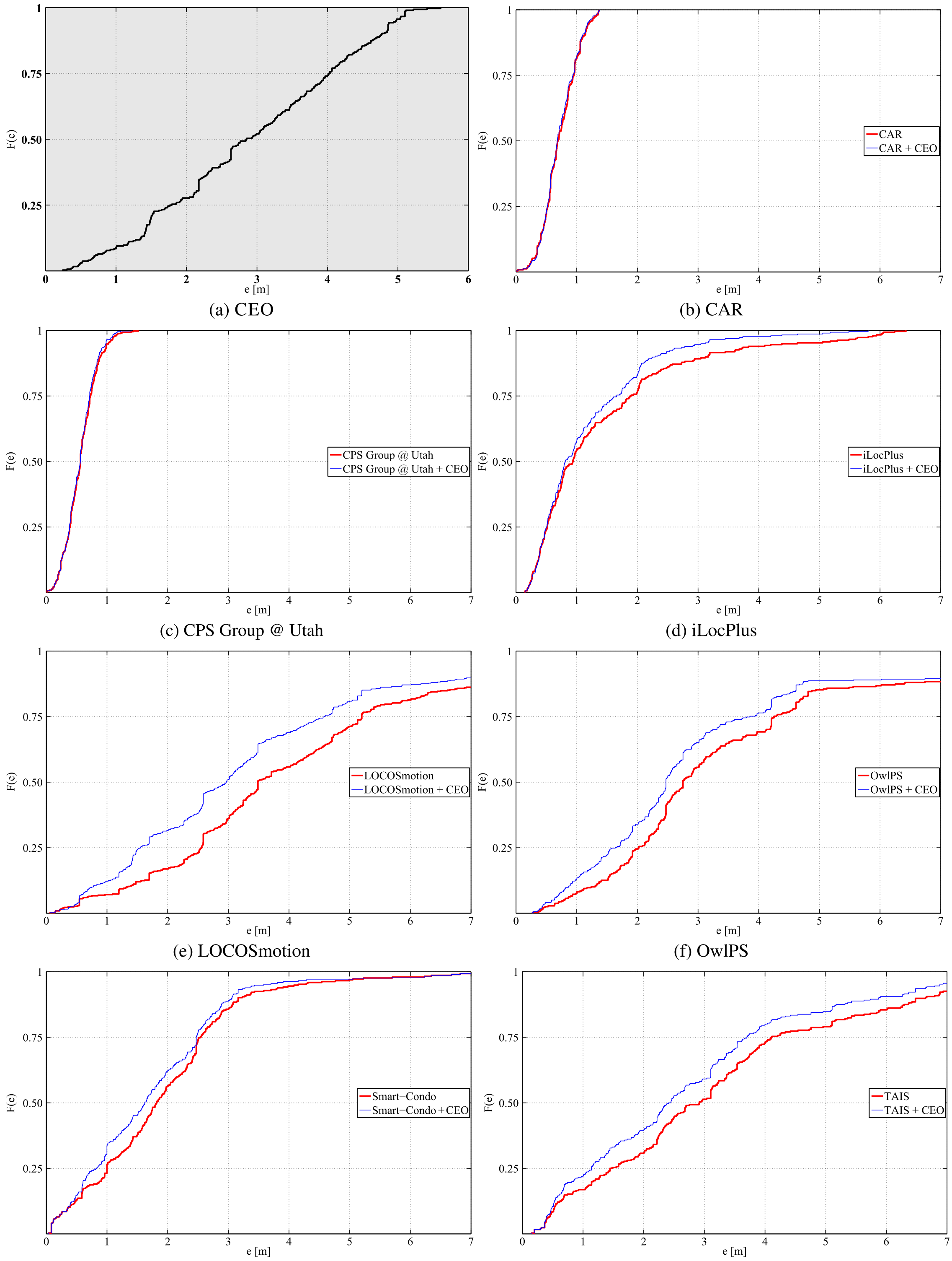
In Table 3 the 75° percentile of estimation error is shown for each competing system, for each path and overall. Next to the error is the variation obtained after fusing the competitor's trace with CEO: most variations are negative or null, indicating an improved performance, while positive variation are always less than ten centimeters.

As it should be expected, the best performing systems show no or very little improvements after fusion with CEO: CAR and CPS Group in 2012, RealTrac in 2013, show no visible improvement. Systems that used the context info, that is Smart-Condo in 2012 and LOCOSmotion in 2013, also exhibit little improvement.

On the other hand, the worst-performing systems as far as accuracy is concerned show the highest improvements after fusing with CEO. Improvements are sometimes significant, with values greater than 35 cm in three cases in 2012 and two cases in 2013. In particular, LOCOSmotion in 2012 and SHMPS in 2013, which internally have used some form of data fusion, could have significantly benefited from the context info at very little cost, yet disregarded this possibility.

6. Conclusions

We have shown that using low-cost, low-quality context information for obtaining or improving an estimate of a user position in an indoor AAL environment is a real possibility. We have considered the EvAAL competition as an example, a controlled yet realistic situation where an actor moves in a living lab, along a completely instrumented path, with a movement pattern compatible with an AAL scenario. A number of



(a) CEO (b) CAR (c) CPS Group @ Utah (d) iLocPlus (e) LOCOSmotion (f) OwlPS (g) Smart-Condo (h) Tais

Fig. 9. Error distribution for all competitors in 2012 with and without fusion with CEO.

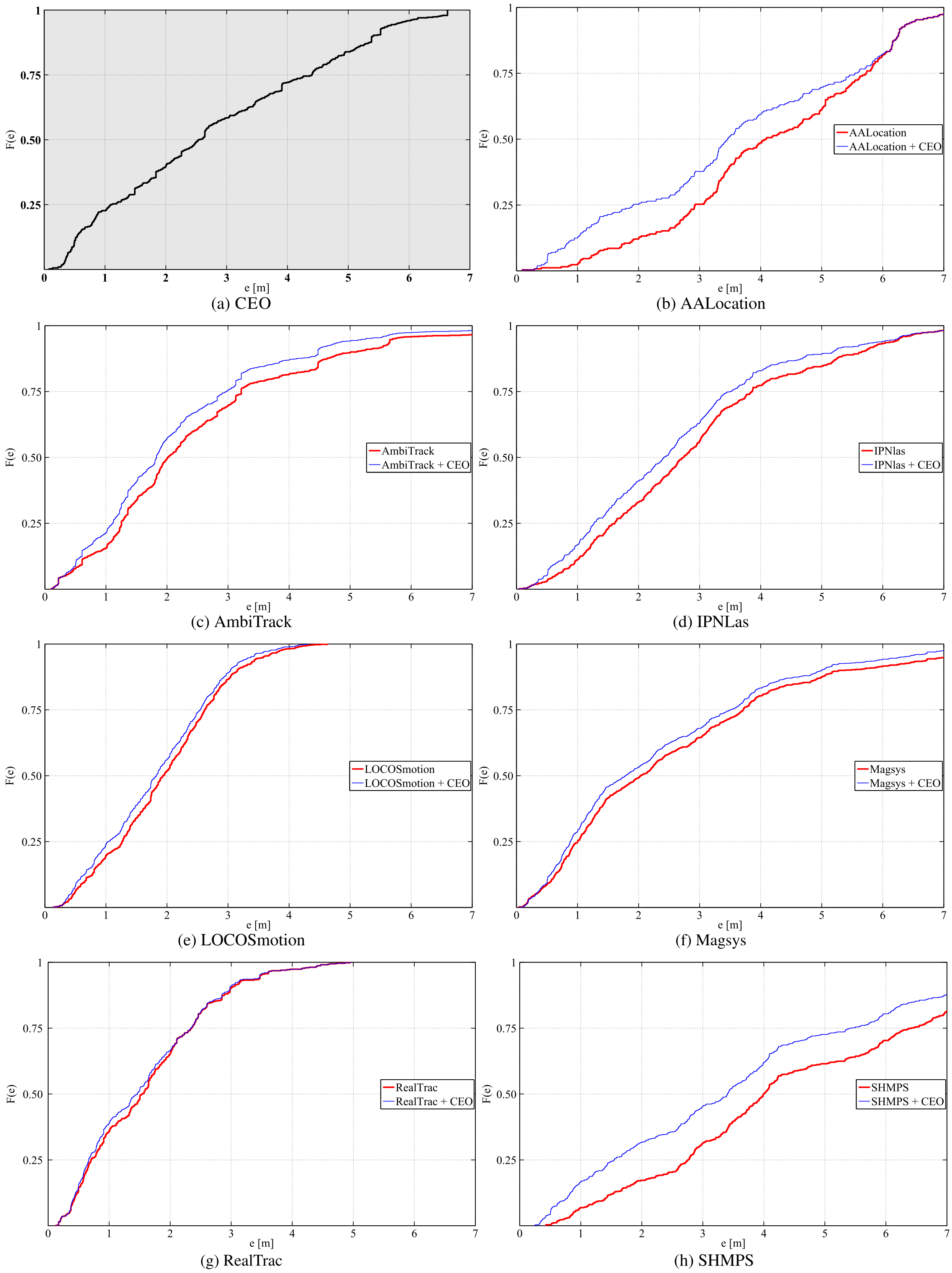


Fig. 10. Error distribution for all competitors in 2013 with and without fusion with CEO.

Table 3

Third quartile error of competing systems and its variation after fusion with CEO – negative variations indicate improved performance

Year	Competitor	Overall		Path 1		Path 2		Path 3	
2012	CAR	0.95	−0.02	0.77	+0.00	1.00	−0.01		
2012	CPS Group @ Utah	0.73	−0.01	0.75	−0.02	0.71	−0.01		
2012	iLocPlus	1.88	−0.23	2.03	−0.04	1.75	−0.16		
2012	LOCOSmotion	5.20	−0.61	4.71	−1.19	5.43	−0.30		
2012	OwlPS	4.25	−0.40	4.62	−0.42	4.21	−0.84		
2012	Smart-Condo	2.54	−0.07	2.32	−0.02	2.65	−0.14		
2012	TAIS	4.10	−0.40	3.99	−0.59	4.25	−0.38		
2012	**CEO**	4.02		4.07		3.94			
2013	AALocation	5.73	−0.18	3.68	−0.03	4.65	−1.98	5.92	−0.00
2013	AmbiTrack	3.22	−0.24	2.43	+0.00	2.82	+0.00	4.47	−1.17
2013	SHMPS	6.42	−0.99	3.80	+0.00	4.78	−0.55	7.20	−0.53
2013	IPNlas	3.86	−0.36	3.81	−0.05	5.34	−1.31	3.17	−0.03
2013	LOCOSmotion	2.62	−0.07	2.21	−0.06	2.89	−0.15	2.61	−0.03
2013	Magsys	3.71	−0.21	3.84	+0.00	3.11	−0.10	3.95	−0.65
2013	RealTrac	2.35	−0.00	3.06	−0.08	2.07	+0.08	1.83	+0.00
2012	**CEO**	4.40		4.93		3.21		4.71	

real-time localization systems installed in the environment and on the user, all using different technologies implemented independently, were evaluated and compared.

The performance of the competing systems was put side by side with CEO, and the results appear comparable, at least for the scenarios that included a single person moving in the AAL environment.

In addition, CEO was coupled with each system in a straightforward way to demonstrate how a small software-only addition can improve the performance of heterogeneous systems by data fusion with low-quality, binary-only context information.

We should conclude that even little information such as that provided by light switches, intrusion detection systems or possibly by non-intrusive load monitoring (NILM) systems [11,47,49] can be precious, as it is provided for free and can be exploited by a software-only system that can be embedded in the AAL infrastructure.

Moreover, if a dedicated localization system is in place, it can generally benefit with little effort from the added information provided by the devices already present in the environment. If the localization system internally uses any sort of information fusion, as it is often the case and as it will more and more often in the future, the effort of integrating the context information is very low, while providing an improvement of performance in most cases.

Future work should be oriented at implementing a system based on the presented concepts, starting with the simple case of a basic domotic environment where light switches, intrusion detection system and possibly home appliances generate events on a domotic home network. One possibility is to test the concept on more extensive real data gathered from real test sites provided by the EU FP7 GiraffPlus project [10] and other living labs from EU FP7 DOREMI project[7], when they become available.

As a final remark, we propose that, in the next EvAAL competitions, the value of localization accuracy provided by the CEO algorithm is considered as the minimum acceptable value to be provided by competing systems.

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