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Monitoring elderly behavior via indoor position-based stigmergy

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A B S T R A C T

In this paper we present a novel approach for monitoring elderly people living alone and independently in their own homes. The proposed system is able to detect behavioral deviations of the routine indoor activities on the basis of a generic indoor localization system and a swarm intelligence method. For this reason, an in-depth study on the error modeling of state-of-the-art indoor localization systems is presented in order to test the proposed system under different conditions in terms of localization error. More specifically, spatiotemporal tracks provided by the indoor localization system are augmented, via marker-based stigmergy, in order to enable their self-organization. This allows a marking structure appearing and staying spontaneously at runtime, when some local dynamism occurs. At a second level of processing, similarity evaluation is performed between stigmergic marks over different time periods in order to assess deviations. The purpose of this approach is to overcome an explicit modeling of user's activities and behaviors that is very inefficient to be managed, as it works only if the user does not stray too far from the conditions under which these explicit representations were formulated. The effectiveness of the proposed system has been experimented on real-world scenarios. The paper includes the problem statement and its characterization in the literature, as well as the proposed solving approach and experimental settings.

Keywords:

Ambient Assisted Living
Indoor localization
Marker-based stigmergy
Swarm intelligence
Elderly monitoring

1. Introduction and motivation

Recent prospects of the world population show clear trends tending towards more elderly people and single households [1], which have substantial effects on public and private health care, emergency services, and the individuals themselves. In this context, Ambient Assisted Living (AAL) is currently one of the most important research and development areas. It aims at applying ambient intelligence technology to enable people with specific demands and elderly to live in their preferred environment longer and safer [2].

The possibility of monitoring the health status of elderly people living alone in their houses is a core service of AAL scenarios [3]. This possibility optimizes the prevention of emergencies, which can have important effects on public and

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private healthcare services. Examples of emergencies are falls, leading to immobilization, cardiac arrest, or helplessness: when unnoticed for hours, they may lead to severe follow-up complications. Age-related chronic diseases, such as dementia, depression, cardiac insufficiency, or arthritis, can be faced in a proactive and preventive way in order to let patients take advantage of more adequate assistance services [4,5].

Among the possible physical conditions to be monitored by an automatic monitoring system in AAL scenarios, emergency situations and chronic diseases are the most relevant. These two kinds of situations can be clearly distinguished on the basis of different perspectives. Prompt detection and timely notice are fundamental requirements of an emergency, which usually occurs in a short time. In contrast, a disease is characterized by a gradual detection of long-term deviations from the typical behavior or by critical trends in the user's vital parameters. Active user involvement (e.g. pressing buttons on wearable alarm devices) can be appropriate while dealing with an emergency, but it is not acceptable for disease situations, which are initially characterized by a lack of noticeable symptoms and then by the absence of an emotional involvement that could activate decision-making.

In the literature of AAL, a number of systems have been developed for automatic detection of in-home situations, embracing two broader paradigms: Context Awareness and Ambient Intelligence [6–8]. In AAL systems, data sources can be different parametric sensors (e.g., location, movement, interaction, vital data, etc.), which feed a multi-level and hierarchic processing [6]. There are many possible parameters, derived from sensors that can be intrusive and whose management costly. Moreover, their tracking is often related to specific situations to detect. In practice, monitoring elderly behavior in real-time requires choosing a trade-off between what to monitor and how to notice it. Actually, much work still has to be done before such systems can be used on a regular basis. One of the most important lessons learned from these efforts is that the parametric aggregation must use a limited amount of states, be highly flexible and able to handle uncertainty [4,9,10].

When dealing with uncertainty, the logic of automatic detection is intrinsically different between emergency and disease. An emergency event can either be true or false. As a Boolean event, the single emergency has no doubt in the human experience. Uncertainty arises in an automatic system from the question whether or not the system perception correctly classified the event. The system assessment can be based on the frequency that an event is actually true or false over a high number of cases. Instead, in a disease situation, uncertainty is an aspect of human experience, characterized by a “gray zone” where the situation can be classified as both true and false. The system assessment can be based on the similarity degree of an event to the two classes, based on the proximities of an observation to the different truths. The final point is that emergency modeling involves conventional single-valued classification, whereas disease modeling involves multi-valued classification. Another relevant difference between emergency event and disease situation is related to the standardization versus personalization of the logic. When detecting emergency events, it is relatively easy to reuse logic for many individuals. In contrast, there are significant differences between individuals when detecting disease situations.

In this paper we propose a novel approach to unusual behavior detection, with a focus on disease situations. In the literature of behavioral monitoring and health state assessment, a great standardization effort has been done by means of the so-called Activities of Daily Living (ADL). ADLs are daily activities carried out by individuals, such as feeding, dressing, sleeping, walking, watching TV, etc. [11,12], which act as a basis to represent habits of healthy people. Health professionals can thus refer to the ability or inability to perform ADLs as a measurement of the functional status of people with disabilities.

Most AAL research is currently carried out with the purpose of allowing software systems/agents to detect ADLs on the basis of suitable processing, reasoning and manipulation of sensors data. One of the most important sources of information to infer ADLs is the position of the elderly moving in his home during daily living activities. While in outdoor scenarios Global Positioning System (GPS) constitutes a reliable and easily available technology, in 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 [13,14]. In the literature, each solution has advantages and shortcomings, which, in most cases, can be summarized in a trade-off between precision and installation complexity (and, thus, costs). The proposed approach to unusual behavior detection aims at overcoming the inherent imprecise output of a localization system implementing a source-agnostic software infrastructure. The main goal is to be able to handle position information coming from any kind of localization system with different accuracies and precisions. In order to assess the proposed solution in dealing with different localization systems, we modeled the localization error of real indoor localization systems in order to use it as a test of reliability and insensitiveness to perturbations on the input data.

Many efforts in the AAL field aimed at supporting system-oriented analyses based on mathematical and logical models. Typically, this approach deploys an arsenal of techniques, including machine learning and probabilistic modeling, in the attempt to deal with the inherent complex, user-dependent, time-varying and incomplete nature of human-driven sensory data and behavioral logic. Another important problem of this approach is that domain modeling raises proprietary and privacy concerns, due to the direct access and processing of personal data sources and to the modeling of personal behavior. We call this approach *cognitivist*, because the domain model is a formalized description synthesized by a cognitive task of a human designer [15]. The representation of a functional or logical structure is then predicated on the descriptions of the designer.

In this paper, we adopt a new modeling perspective, which can be achieved by considering a different design approach: *emergent* [15]. With an emergent approach, the focus is on the low level processing: sensory data are augmented with structure and behavior, locally encapsulated by autonomous subsystems, which allow an aggregated perception in the environment. Emergent paradigms are based on the principle of the self-organization of the data, which means that a functional structure appears and stays spontaneous at runtime when local dynamism occurs. Emergent approaches

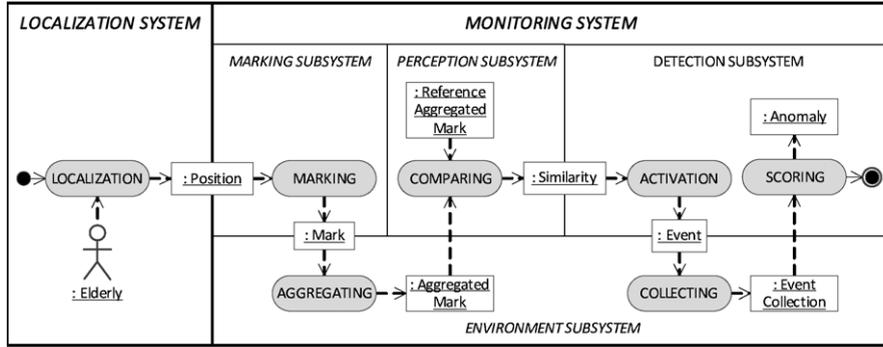


Fig. 1. UML activity diagram of the macro activities of the proposed approach to anomaly detection.

represent the application of biologically-inspired patterns to software design. The purpose is to overcome explicit top-down domain-dependent representations of data, which are more efficient to be computed but more inefficient to be managed in the entire lifecycle. By using an emergent paradigm, the collective properties or interactions between sensory data can be described with a domain-independent spatiotemporal logic.

The fact that simple individual behaviors can lead to a complex emergent behavior has been known for decades. It has been noted that this type of emergent aggregated behavior is a desirable property in pervasive computing [16,17]. For instance, in [18] stigmergy has been used for tracing the intelligent navigation of people in ubiquitous computing environments. Here the idea of digital pheromone trails is adopted with the purpose of finding the optimal route from the history of people's behavior. Although the problem considered is different with respect to our problem, the paper is an example of implementation of the emergent paradigm with stigmergy: to find the answer to a problem in people's emergent behavior, rather than in the environment via a cognitivist strategy.

In this paper, we show how an emergent approach can be implemented by discussing a multi-level scheme for the detection of disease situations, structured into four levels of information processing. The first level is managed by a generic localization system with different accuracies and precisions. The second level is in charge of a marking subsystem leaving marks in the environment in correspondence to the position of the person. The accumulation of marks creates an aggregated mark, observed by a perception subsystem, which compares the current aggregated mark with a reference aggregated mark. The reference aggregated mark is a stigmergic track, sampled in a period determined by a relative and a healthcare professional, in which the elderly is stable in her health conditions. Finally, a detection subsystem processes the similarity in order to extract indicators of a behavioral change. For a better distinction of the progress of unfolding deviation events, we adopt a smoothed activation function for behavioral changes. Fig. 1 shows an UML activity diagram of the overall information processing. Here, the *localization* and the *monitoring* systems are represented as a rectangle. The monitoring system is in turn made of the subsystems: *environment*, *marking*, *perception*, and *detection*. Activities (represented by gray oval shapes) are connected via data flow (dashed arrow) through input/output data objects (white rectangles). The black circle represents the initial step, while the black circle with white border represents the final step. More specifically: (i) *localization* takes a person (in our scenario, the elderly) and provides his position; (ii) *marking* takes a position and produces a mark; (iii) *aggregating* takes marks and provides aggregated marks; (iv) *comparing* takes reference and aggregated marks and provides similarity between them; (v) *activation* takes similarity and produces events; (vi) *collecting* takes events and produces event collections; (vi) and finally *scoring* takes event collection and provides anomaly.

The system does not characterize specific disease situations: it alerts relatives or healthcare professional on a behavioral change that might be better investigated in person. This strategy is characterized by the use of an unobtrusive positioning system, a very standardized logic, and a broad-spectrum monitoring. We prove that the proposed technique is quite insensitive to the different levels of localization error. The paper is organized as follows. Section 2 covers the related work on monitoring the elderly behavior. Section 3 shows the error modeling process for real indoor localization systems. The monitoring system is discussed in Section 4. In Section 5, experimental studies are presented, while Section 6 draws the final conclusions.

2. Monitoring elderly behavior: related work

There are many settings in which Ambient Intelligence can greatly impact on our lives, enriching environments to create "smart homes". Several artifacts and items in a house can be enriched with sensors to gather information about their use and in some cases even to independently act without human intervention [19]. The main expected benefit of this technology is the increasing safety of people with specific demands and elders. By monitoring lifestyle patterns or the latest activities and providing assistance when a possibly harmful situation is developing, a smart home realizes the so-called Ambient Assisted Living paradigm [9].

With the maturity of sensing and pervasive computing techniques, extensive research is being carried out in using different sensing techniques for understanding human behavior [20]. Behavior modeling can be realized through different

approaches. Probabilistic models are the most common. Discriminative approaches, as well as approaches based on behavior pattern clustering and variability, are also used. The main distinction among these techniques is the modality of inferring the context and identifying an emergency or significant situation in the user's behavior: sensor data-driven and knowledge-based methods [21]. The former approach faces the problem of the recognition of human activities and the detection of anomalies during their performance by using the information provided by sensors in order to build, infer, or calibrate a behavior model [22]. Machine-learning techniques have been extensively used with this purpose, and, more specifically, probabilistic models [23,24], data mining [25,26], and inductive learning [27,28]. The latter are systems equipped with semantic tools, in which well-defined meaning is given to context information so that it enables computers and people to work in cooperation. Semantic tools for the recognition of human behavior are represented by ontologies models enabling reasoning, information sharing, and knowledge representation [29].

In both data-driven and knowledge-based approaches for monitoring the elderly behavior, an important role is played by the information gathered from the position of the user in the home over a long period of time. Several research works have been conducted in indoor localization in order to offer solutions in elderly care facilities. These solutions are based on dedicated positioning sensors, like pyroelectric infrared detectors (PIR) and magnetic sensors [30], fall sensors [31], wireless sensor networks and radio frequency identification (RFID) sensors [32], and off-the-shelf conventional home automation sensors [33].

All the cited techniques use the earlier defined *cognitivist* approach, as they apply a domain model to the data that are strictly related to the type of sensors used or to the a-priori semantic knowledge applied. In the literature, effort has been spent in order to create unsupervised algorithms for the analysis of human behavior in homes equipped with sensor networks, but in any case bound to a specific domain model. Models based on Latent Dirichlet Allocation (LDA), which can detect patterns in sensor data in an unsupervised manner, have been proposed in [34]. Another interesting system has been presented in [35], where a human behavioral model is constructed according to observed distribution laws of presence activations in specific rooms. The model is able to detect behavioral deviations in comparison to the resident own habits using the Chebyshev inequality, which makes no assumption about the shape of the data distributions but it uses the knowledge of the rooms and the sensors' placement as an a priori information. A hybrid *cognitivist/emergent* approach has been proposed in [36], where a data mining algorithm is applied to a set of rules (associations between events e.g., "kitchen sink cold water on", "kitchen sink cold water off", "dishwasher open", "dishwasher closed", and "dishwasher on") in order to discover emergent inter-transaction associations rules. Also in this case, however, the proposed technique starts from an a-priori knowledge of the events.

3. Error modeling of indoor localization systems

Localization is a key component for achieving context-awareness. Recent years have witnessed an increasing trend of location-based services and applications. In most cases, however, location information is limited by the accessibility to Global Navigation Satellite Systems (GNSS), largely unavailable for indoor environments. Recently, an international competition on localization systems for Ambient Assisted Living (AAL) scenarios has been created (EvAAL—Evaluating AAL Systems through Competitive Benchmarking) [37]. The objective of this competition is to reward the best indoor localization system from the point of view of AAL applications [38].

In this paper we selected the three best localization systems presented at EvAAL, namely CPS [39], n-Core [40], and RealTrac [41], and we used the estimated positions by these systems as an input to the monitoring system. The description of their systems is as follows:

- CPS is a device-free localization and tracking system, where people to be located do not carry any device. It is based on a wireless sensor network that uses a tomographic approach to localize the users. A static deployed wireless network measures the Received Signal Strength (RSS) on its links and locates people based on the variations caused by the movements of people.
- The n-Core localization system exploits the RSS and the LQI (Link Quality Indicator) measures between a mobile unit worn by the user and a static deployed ZigBee wireless network. The system applies a set of locating techniques to estimate the position of each mobile unit in the monitored environment. These locating techniques include signpost, trilateration, as well as a fuzzy logic.
- The RealTrac localization system exploits the time-of-flight (ToF) and the RSS measures between a mobile unit worn by the user and a static deployed wireless network. In particular, ToF and RSS measures are processed by the server using a particle filter that also takes into consideration the structure of the building, the air pressure value and the inertial measurement unit data.

In order to evaluate how the proposed stigmergy-based technique performs when applied with a real localization system, we modeled the localization error introduced by the selected localization systems and we apply it to the real positions of the monitored users. The selected traces (pair of coordinates) analyzed to model the localization error introduced by the localization systems were collected during the EvAAL competitions. In particular, the traces are related to a typical AAL scenario where the user is alone in the house, he moves along a path from one room to another, including some waiting points, where the user stands for at least 5 s. Table 1 shows the statistics of the localization systems evaluated during the

Table 1

Performance statistics: mean, variance, and percentiles in meters of the localization error for the selected systems during the EvAAL competition.

	Mean error (m)	Error variance (m)	First quartile (m)	Second quartile (m)	Third quartile (m)
CPS	0.5333	0.0562	0.3658	0.5196	0.7129
n-Core	1.0133	0.2863	0.5939	0.9471	1.2869
RealTrac	1.3525	0.5714	0.8700	1.1891	1.7340

Table 2

Skewness and kurtosis values of the localization error for the selected systems during the EvAAL competition.

	Axis	Skewness	Kurtosis
CPS	x	0.19	2.34
	y	-0.35	3.09
n-Core	x	0.0815	2.1434
	y	0.7479	4.0761
RealTrac	x	-0.22	2.55
	y	-0.19	2.56

Table 3

The parameters chosen for the bivariate Gaussian distributions.

	μ_x	μ_y	Covariance	
CPS	-0.0274	0.0314	0.2283	0.0320
			0.0320	0.1116
n-Core	0.0362	0.4608	0.6240	-0.1026
			-0.1026	0.4783
RealTrac	0.0239	-0.1469	1.1083	-0.1115
			-0.1115	0.7500

EvAAL competition. In particular, the mean, the variance, and the percentiles of the localization error (the distance between the real point where the actor is and the estimated coordinates) are shown.

In order to model the errors that the selected localization systems undergo, we analyze the distribution of the error values of each system. To test the behavior of the localization error, we analyzed about 400 position's measures for each system. Table 2 reports the values of the skewness (a measure of the asymmetry of the probability distribution) and of the kurtosis (a measure of the shape of a probability distribution) for the error along the x and the y direction, respectively. As shown in Table 2 the skewness and kurtosis values are near to 0 and 3, respectively (except for the n-CORE system along the y direction). This indicated that the probability distribution function (hereafter PDF) of the error along the x and the y direction should follow the Gaussian distribution.

Figs. 2, 3, and 4 show the scatter plots of the estimated coordinates together with the histogram bar plots evaluated along the x - y directions, for each localization system. From this preliminary analysis we supposed that a bivariate Gaussian distribution could model the error distribution of the selected localization systems. Indeed, we superimpose to each scatter plot a bivariate Gaussian distribution with mean and covariance shown in Table 3 and estimated from the traces collected during the EvAAL competition.

If a set of variables is distributed as a multivariate normal, then each variable must be normally distributed. However, when all individual variables are normally distributed, the set of variables may not be distributed as a multivariate normal [42]. Hence, testing each variable for univariate normality only is not sufficient. The best-known method of assessing the degree to which multivariate data deviate from multinormality is the Mardia's tests [43]. This method allows testing the null hypotheses that the traces are compatible with the assumption of multinormality, based on sample measures of multivariate skewness and kurtosis. Moreover, we tested the assumption of multinormality by using also other two tests: the Kolmogorov-Smirnov [44] and the Doornik-Hansen [45] normality test. The Kolmogorov-Smirnov statistic quantifies a distance between the empirical distribution functions of two samples, while the Doornik-Hansen is a powerful alternative to the Shapiro-Wilk test and, like the Mardia's test, is based on the skewness and kurtosis of multivariate data.

In Fig. 5 the chi-square quantile-quantile plot is shown. For each localization system, we plot the squared Mahalanobis distances against corresponding quantiles of the limiting chi-square distribution. If data are distributed as a multivariate normal, then the points should fall on a straight line with slope one and intercept zero. Outliers can be visually detected; indeed, they will show up as points on the upper right side of the plot for which the Mahalanobis distance is notably greater/lesser than the chi-square quantile value.

Although the localization errors exhibit distributions which slightly deviate from a multivariate normal distribution (Figs. 2, 3, 4, and 5), we verified that the localization errors have been corroborated to be bivariate Gaussian distributed. Indeed, we successfully test, at 0.025 significance level, that the error traces and the bivariate Gaussian distributions (with

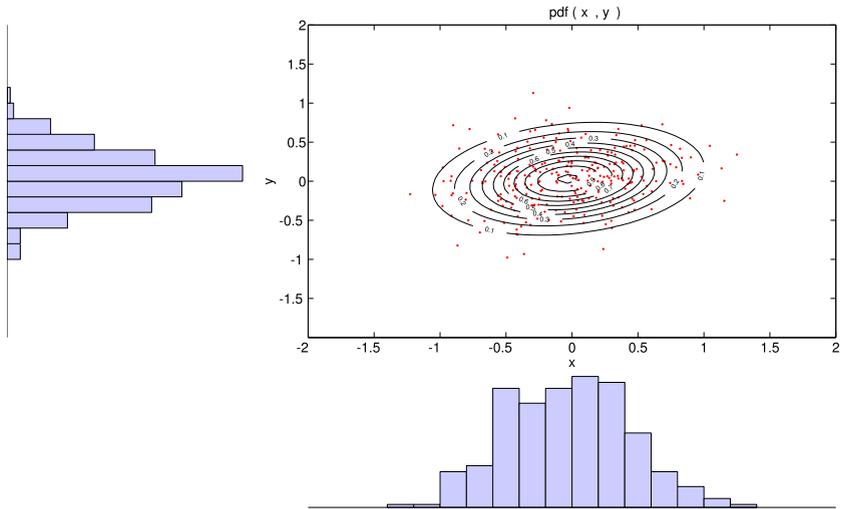


Fig. 2. Scatter and histogram bar plots of the CPS localization system.

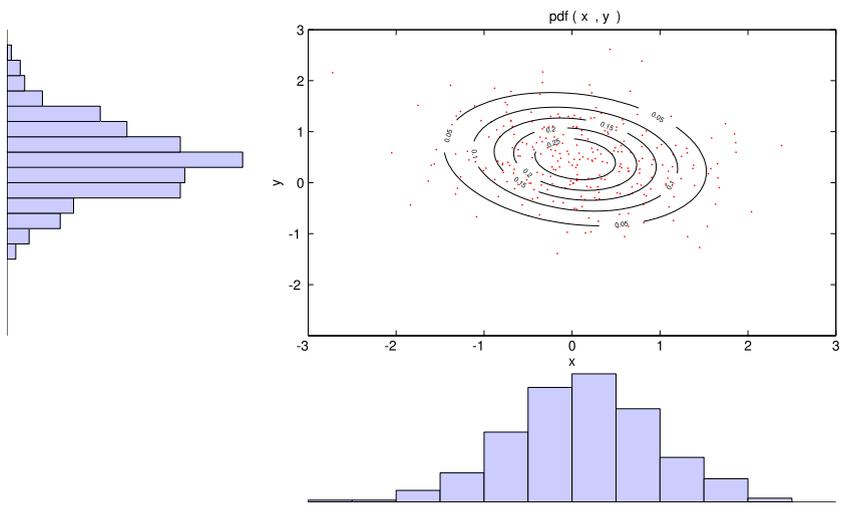


Fig. 3. Scatter and histogram bar plots of the n-Core localization system.

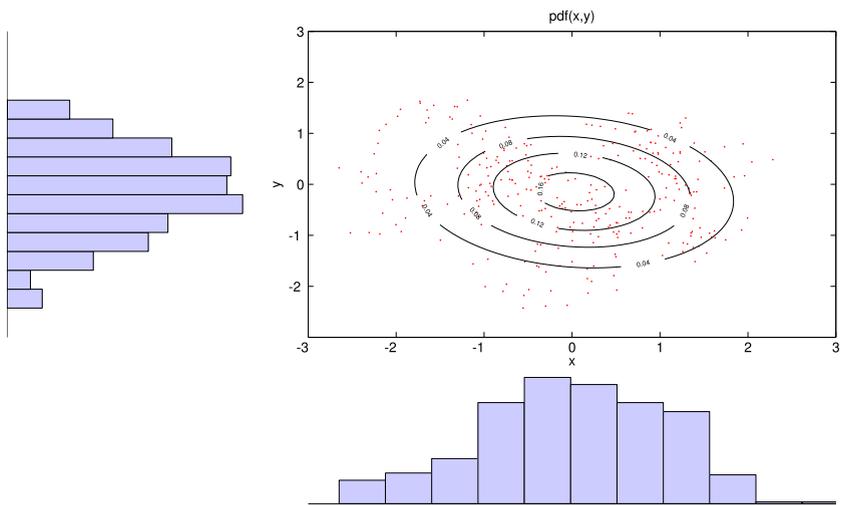


Fig. 4. Scatter and histogram bar plots of the RealTrac localization system.

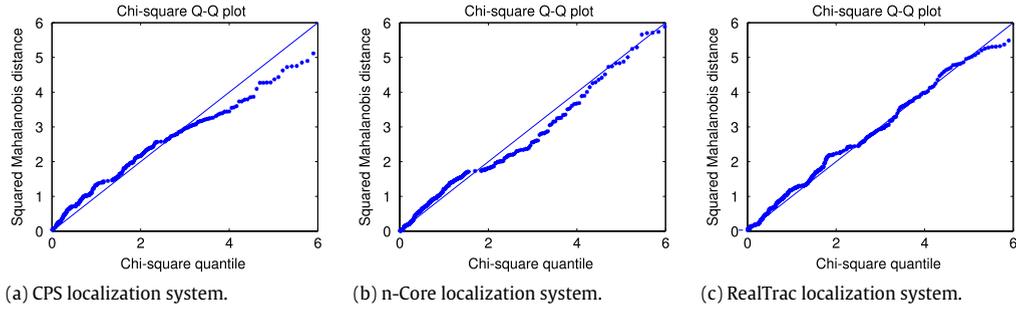


Fig. 5. Quantile–quantile plot of the squared Mahalanobis distance versus the corresponding quantiles of the chi-square distribution.

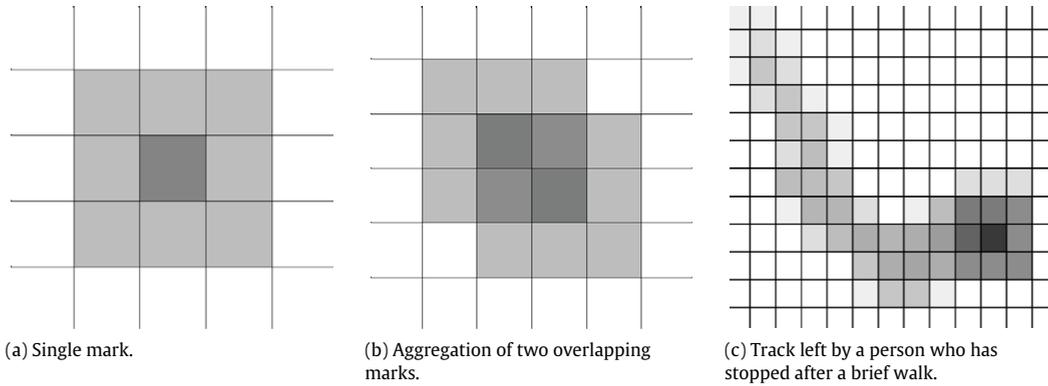


Fig. 6. Basic scenarios of the marking process.

the parameters estimated in [Table 3](#)) pass the Mardia, the Doornik–Hansen, and Kolmogorov–Smirnov tests. From hereon, we will assume that the bivariate Gaussian assumption of the localization error is valid.

4. The monitoring system

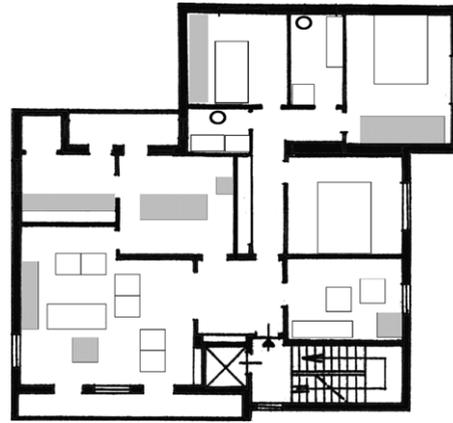
In this section, we report on the monitoring system, designed according to the emergent paradigm. More specifically, we adopt the principles of the marker-based *stigmergy*, which, in social insect colonies, employs chemical markers (pheromones) that the insects deposit on the ground in specific situations. Multiple deposits at the same location aggregate in strength. Members of the colony who perceive pheromones of a particular flavor may change their behavior. Pheromone concentrations in the environment disperse in space and evaporate over time, because pheromones are highly volatile substances.

Marker-based stigmergy can be employed as a powerful computing paradigm exploiting both spatial and temporal dynamics, because it intrinsically embodies the time domain. Moreover, the provided mapping is not explicitly modeled at design-time and then it is not directly interpretable. This offers a kind of information blurring of the human data, and can be enhanced to solve privacy issues. Furthermore, analog data provided by marker-based stigmergy allows measurements with continuously changing qualities, suitable for multi-valued classification.

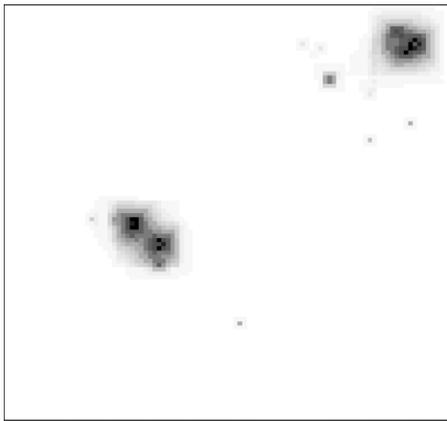
4.1. The marking process

In the *marking* process, a mark structure is encapsulated by a marking subsystem. A marking subsystem takes as an input coordinates generated by the localization system at the micro-level and leaves marks in a computer-simulated spatial environment, thus allowing the accumulation of marks. Consider the entire localization error model as the input for the marking subsystem implies a lot of statistical processing that needs to be done prior to deploying the actual AAL monitoring system and will impact the applicability of the proposed system in new environments, where different localization solutions may be available. While the marking process need to be transparent and not tied up to a specific localization system.

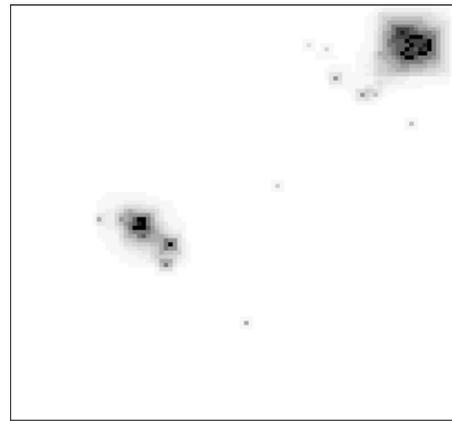
[Fig. 6](#) shows some basic scenario of the marking process. More specifically, [Fig. 6\(a\)](#) shows the structure of a single mark. The levels of mark intensity are represented by different gray gradations: the darker the gradation is, the higher the intensity of the mark. The highest intensity of the mark, I_{MAX} , is in the middle, which corresponds to the position of the person when the mark is left. Mark intensity decreases with the number of squares from the position of the person, of a percentage σ



(a) Pilot scenario: layout of the apartment.



(b) Stigmergic track in a normal day.



(c) Stigmergic track in a day with disease progression.

Fig. 7. Two scenarios of marking process in a real-world apartment with an elderly with some risk of disease progression.

(called *spatial decay*) for each square. Further, mark intensity has a *temporal decay*, i.e., a percentage τ of decrease after a period of time. Hence, an isolated mark after a certain time tends to disappear.

Marks are periodically left by the marking subsystem, with frequency ν . The time that a mark takes to disappear is longer than the period used by the marking subsystem to release a new mark. Hence, if the user is still in a specific position, new marks at the end of each period will superimpose on the old marks, thus increasing the intensity up to a stationary level. It can be demonstrated that the exact superimposition of a sequence of marks yields the maximum intensity level to converge to the stationary level I_{MAX} / τ [46]. If the person moves to other locations, consecutive marks will be partially superimposed and intensities will decrease with the passage of time without being reinforced. Fig. 6(b) shows two consecutive and overlapping marks, and Fig. 6(c) shows the track left by a person who has stopped after a brief walk. The area with the highest intensity (on the right bottom) corresponds to the place where the person is still. The track with lower intensity is the area where the person was moving. Thus, when the person is still, the superimposition of marks causes their intensities sum up, and then the resulting intensities tend to be higher than in other places.

The stigmergic track can then be considered as a short-term and a short-size action memory. The marking level allows capturing a coarse spatiotemporal structure in the domain space, which hides the complexity and the variability in data. As a real-world pilot scenario, Fig. 7(a) shows the layout of an apartment where an elderly with some risk of disease progression has been monitored. Here, a black or gray region represents non-walkable areas (e.g., wall, wardrobe, TV, etc.), whereas a white region represents an area where the person can walk or stay (e.g., floor, bed, armchair, etc.).

Fig. 7(b) shows the stigmergic track generated in the morning of a normal day, for two hours and a half, up to 10.30 A.M. Here, a relevant intensity is located on two points of the apartment, which might correspond to Point of Interest (POI). Fig. 7(c) shows the stigmergic track generated in the same day of the week for the same timetable, when the person had disease symptoms. Here, top-right track is larger and the bottom-left track is smaller than the corresponding track in the normal day of Fig. 7(b).

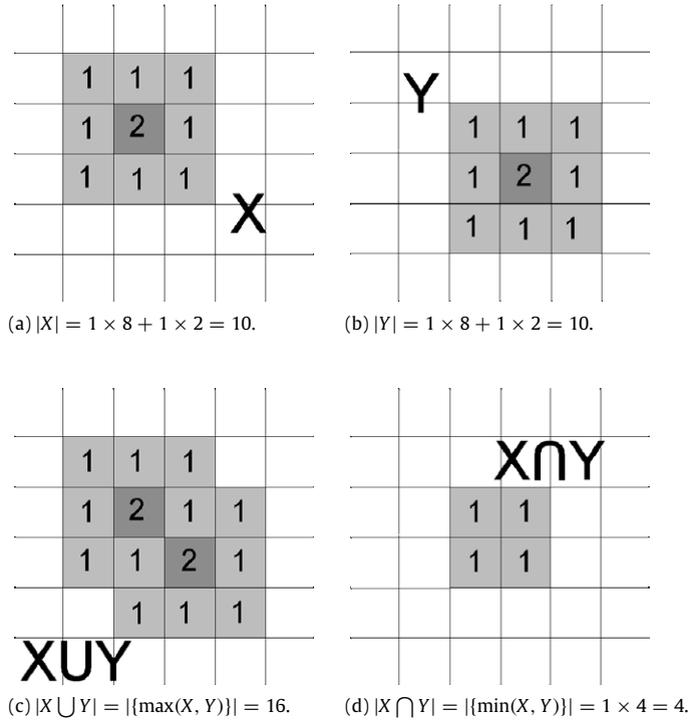


Fig. 8. An illustrative example of similarity between two consecutive marks, $S = |X \cap Y|/|X \cup Y| = 4/16 = 0.25$.

In the above example, it is clear that a stigmergic track provides comprehensive information that can be handled to automatically detect behavioral changes without explicit activity modeling, with simple processing, and preserving privacy. An in-depth (cognitivist) investigation reveals that the above-mentioned disease's symptoms are sleep changes and loss of energy, causing more sleep and late breakfast, with a shift of about 20 min with respect to the normal day. Indeed, the two major tracks are placed on the bed (top-right) and on the living room (bottom-left).

4.2. The perception process

At the second level there is the *perception* process, consisting of the sensing of the track accumulated in the environment at the macro-level. Here, we take advantage of stigmergy (computed at the first level) as a means of information aggregation of the human spatiotemporal tracks. Indeed, the process of information aggregation is a vehicle of abstraction, leading to the emergence of high-level concepts beyond occurring fluctuations. Such fluctuations can be caused by the underlying localization system, but mostly by physical, mental, cultural, and lifestyle differences between individuals. The perception subsystem performs a comparison, called *similarity*, between the current and a reference track. In other terms, similarity aims at sensing the variation of the current behavior situation with respect to what was judged a normal behavior. The normal behavior of the elderly is established in a period of stable health conditions by a relative and a healthcare professional. Of course, since the normal behavior can change in the long-term, the related reference track can be updated when necessary.

Fig. 8 shows a three-dimensional representation of the similarity implemented by the perception subsystem. Formally, given two marks X and Y , their similarity is a real value calculated as the volume covered by their intersection ($X \cap Y$ in the figure) divided by the total volume (the union of them). The lowest similarity is zero, i.e., for tracks with no intersection, whereas the highest is one, i.e., for identical marks.

Fig. 9 shows an illustrative example of similarity between tracks. More specifically, Fig. 9(a) shows the track of Fig. 6(c), whereas Fig. 9(b) shows the same track shifted two cells right and two down. Fig. 9(c) and (d) shows their intersection and union, respectively.

Fig. 10 shows the similarity values in a time frame of about 6 h, between a track in a normal day of the week and a track in the same day of the week with a disease progression. A sample of the two tracks in a specific instant of time is shown in Fig. 7(b) and (c). Here, the reduction in the similarity values in the interval 90–130 is due to the differences discovered in Fig. 7(b) and (c).

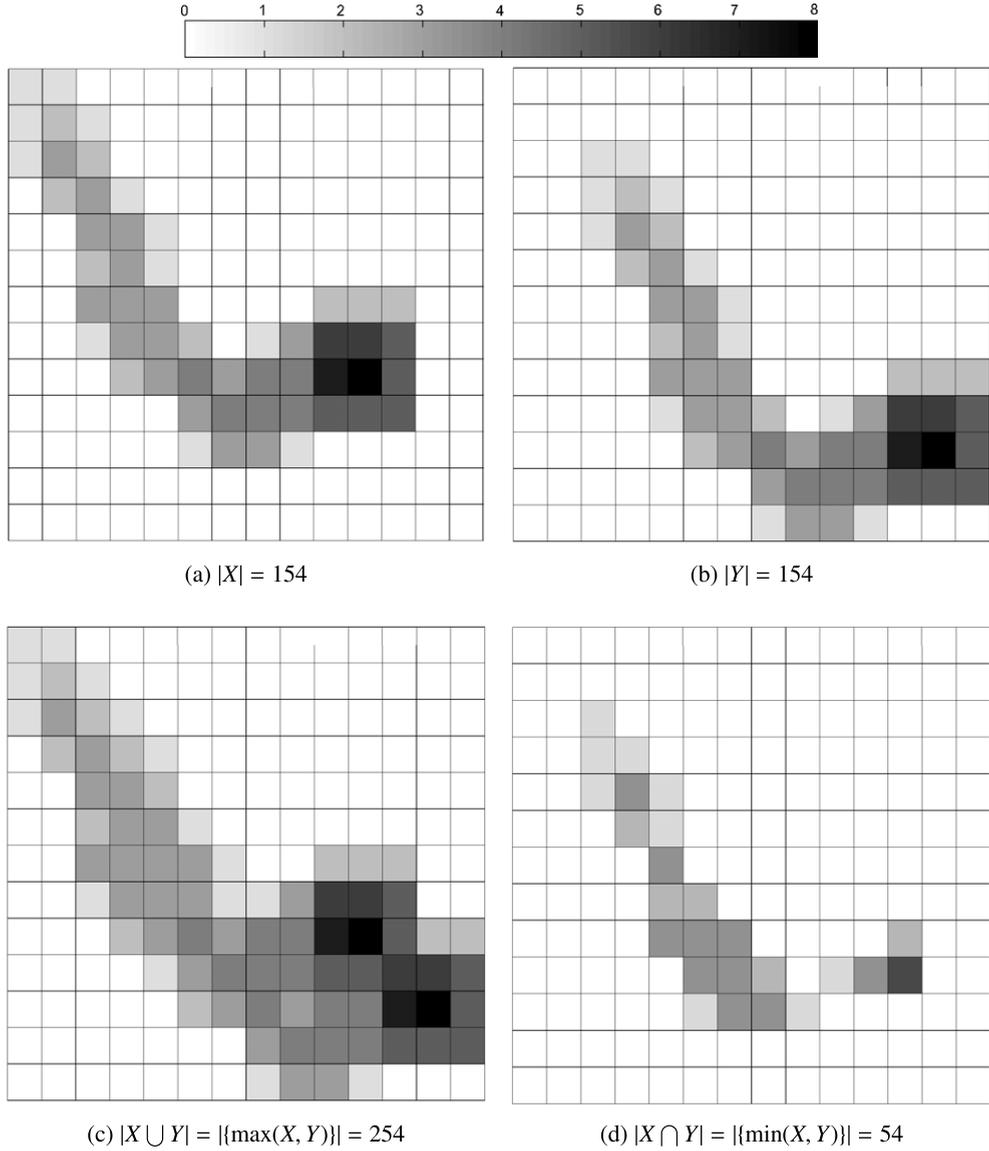


Fig. 9. An illustrative example of similarity between tracks, $S = \frac{|X \cap Y|}{|X \cup Y|} = \frac{54}{254} = 0.21$.

4.3. The detection process

The anomaly detection is handled at the third processing layer, called *detection*, involving the discovery of patterns from the similarity provided by the perception layer. The detection subsystem provides a domain-related output. More specifically, we apply to similarity a smoothed activation function. The term “activation function” is taken from the neural sciences and it is related to the requirement that a signal must reach a certain level before a processing layer fires to the next layer. A smoothed activation function allows achieving a better distinction of the critical phenomena during unfolding deviation events, with a better detection of progressing levels of the anomaly. For this purpose we employ the *s-shaped* activation function to the similarity output. An example of activation function is shown in Fig. 11, with $\alpha = 0.7$ and $\beta = 0.8$, considering the following definition:

$$f(x) = f(x) = \begin{cases} 0, & \text{if } x \leq \alpha \\ 2 \times \frac{(x - \alpha)^2}{(\beta - \alpha)^2}, & \text{if } \alpha \leq x \leq \frac{\alpha + \beta}{2} \\ 1 - 2 \times \frac{(x - \alpha)^2}{(\beta - \alpha)^2}, & \text{if } \frac{\alpha + \beta}{2} \leq x \leq \beta \\ 1, & \text{if } x \geq \beta. \end{cases} \quad (1)$$

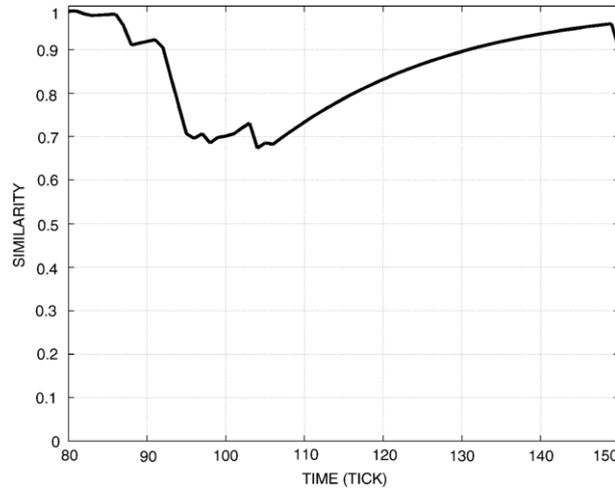


Fig. 10. Similarity function for the two marks represented in Fig. 7 over a time frame of about 6 h.

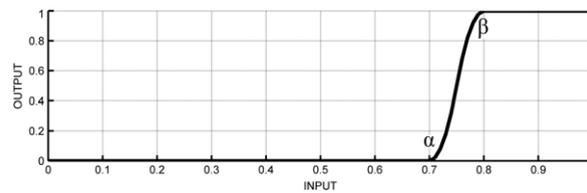


Fig. 11. S-shape activation function with $\alpha = 0.7$ and $\beta = 0.8$.

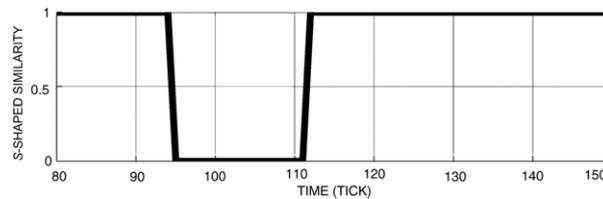


Fig. 12. S-shaped similarity.

Fig. 12 shows the resulting output when applying the activation function of Fig. 11 to the similarity of Fig. 10. As an effect of the s-shape activation function, values lower than α are further decreased, whereas values higher than β are further amplified, in order to evidence major dissimilarity. Each sample of the s-shaped similarity of Fig. 12 is then associated to one of two event classes: *Positive* (i.e., behavioral deviation) and *Negative* (i.e., no deviation). The actual anomaly is established by the *Daily Positive Rate*, an online anomaly score defined as the percentage of positive samples with respect to the total samples of the day. The Daily Positive Rate supports the decision process of the healthcare professional with a kind of augmented perception, because it increases when the normal behavior of the elderly is affected by significant deviations. The next section provides real-world examples and related illustrations of the different processing layers.

5. Experimental studies

This section shows a real-world application on an elderly with some risk of disease progression, living alone in the apartment of Fig. 7(a). The experimentation aims at assessing the effectiveness of the system in recognizing a reliable measurement of the deviations from the routine indoor activities, by applying different localization systems. In order to assess the effectiveness of our system, human-based observation and system-based detection must be connected for each sample of the considered time period. In this way, the results provided by the system could be interpreted thanks to data and metadata provided by the human observation. The following subsections explain how experimental data were collected and how the system assessment was carried out.

Table 4
Main parameters set in the tuning session.

	Symbol	Value
Maximum mark intensity	I_{MAX}	20
Size of the cells grid	-	100×100 cells
Spatial decay	σ	10 cells (≈ 1.4 m)
Temporal decay	τ	0.1 (single mark life ≈ 30 periods)
Marking period	ν^{-1}	5 min
S-shape parameter	α	0.4
S-shape parameter	β	0.4

5.1. The experimental setup

Despite of the advantages of Ambient Assisted Living, identifying human paths in home remains a difficult issue due to privacy-related concerns. In order to preserve the privacy of the patient and to avoid interfering with his daily life, positioning and behavioral data were reported by a relative of the patient. The relative was in charge of observing every week off-line video tracks of the elderly, living alone and independently. The video tracks were provided by a collection of cameras, placed one per room. More specifically, first, continuous video acquisition sessions were made, each lasting for a week. For each week, a list of behavioral deviations occurred in the session was extracted by the relative. After some sessions were collected, two sessions were selected by the relative: a week considered as an healthy period (i.e., with no significant behavioral deviations), and a week with some behavioral deviation. For the two selected weeks, the position of the elderly in the apartment was sampled by the relative, every 5 min (i.e., 12 samples per hour) and with 0.6 m of uncertainty.¹ Thus, we were supplied at most with $24 \times 12 = 288$ actual position samples per day. When the patient is away from home, there are no position samples available and then there is no system output. To assess the robustness of our system, different indoor positioning systems were simulated by taking into account the actual position samples. In order to evaluate how the proposed monitoring system performs with the three different localization systems considered, we took reference locations and added errors according to the models obtained in Section 3. In this way, we derived three cases having exactly the same mobility scenario, but differing on the localization error. Indeed, the purpose of the experimentation is to show that our monitoring system is not sensitive to the particular localization technology.

The healthy session was used as a tuning session, whereas the other session was used for testing. Hence, during the first session, the main parameters were set. Table 4 shows the main parameter values used. More specifically, the spatial decay was set to 10 cells, i.e. about 1.4 m in the discretized marking space of 100×100 cells. Since we want to be independent of the localization systems we chose the mark size equal to the maximum localization error of the analyzed systems. This value represents an upper bound of the localization error along the x direction of the RealTrac system. The setting process of this parameter is quite simple: it depends on the expected position uncertainty of the localization systems. Indeed, 1.4 m proved large enough to cover such uncertainty, while being sufficiently small to distinguish the closest point of interests. The maximum mark intensity is usually provided with the same scale value of the spatial decay (i.e., 20) in order to reduce the approximation errors in computing numbers that have different orders of magnitude. However, the maximum mark intensity is a very insensitive parameter. Temporal decay was set so as to provide sufficient historical memory in a single mark: 30 periods, i.e., 150 min. This duration proved sufficient to cover the largest behavioral deviations occurring with disease progression. Indeed, the setting of this parameter is a two-step process. First, the healthcare professional establishes how disease progression is commonly manifested, and the relative contextualizes such candidate symptoms on the elderly to monitor. This allows establishing an order of magnitude of the parameter value. Second, behavioral deviations are simulated in order to assess a more precise value. In this stage, the low sensitivity of the parameter on the set value is also assessed. More specifically, with the CPS localization system, the system performance (F-measure) calculated with a temporal decay of 0.09, 0.10 and 0.11 are 0.729, 0.728, 0.727 respectively. We set the two s-shape parameters to the same value because both the healthcare professional and the relative established that there are no transients in the expected deviations. In the second phase, significant deviation events are artificially generated to assess a more precise value, and the low sensitivity on the set value has been verified. More specifically, with the CPS localization system, the exact value 0.4 was selected after a very few alternatives determined as follows: the lower bound must be higher than the baseline, whereas the highest bound must fit the most significant deviation events. The baseline is computed by the similarity between two corresponding healthy days of the week, e.g., two Mondays, because it represents the noise generated by micro behavioral differences during a healthy period. Finally, the system performance (F-measure) calculated with α and β equals 0.3, 0.4, and 0.5 are 0.72, 0.73, and 0.69, respectively.

For the reasons above discussed, the approach followed is semi-supervised, because samples are assumed only for normal data. Essentially, a basic setting is established via heuristic supported by the healthcare professional, whereas close-to-optimum values are established by using simulation and sensitivity. This approach avoids configuring a system specialized

¹ For this purpose, the floor of any room was previously labeled with markers visible in the video tracks. To reduce uncertainty, we used inverse perspective algorithm which is very standard in imaging field.

Table 5
Behavioral deviations observed in the testing session.

Id	Day	Start-end (ticks)	Duration (ticks)	Description of the observed behavioral deviation
1	Tue	185–204	20	He had a shorter lunch
2	Wen	096–100	5	He woke up later in the morning
3	Wen	150–158	9	He had a shorter lunch
4	Wen	181–230	50	He had a longer nap and shorter tasks in the afternoon
5	Thu	098–107	10	He woke up later in the morning
6	Thu	150–153	4	He had a shorter lunch
7	Thu	195–240	46	He had a longer nap and shorter tasks in the afternoon
8	Fri	092–095	4	He woke up later in the morning
9	Fri	108–119	12	He carried out less housekeeping tasks
10	Fri	170–173	4	He had a longer nap in the afternoon
11	Fri	190–216	27	He carried out less tasks in the afternoon
12	Fri	246–250	5	He had a shorter dinner
13	Sat	103–107	5	He woke up later in the morning
14	Sat	158–164	7	He had a shorter lunch
15	Sat	188–242	55	He had a longer nap and shorter tasks in the afternoon
16	Sun	109–113	5	He woke up later in the morning
17	Sun	119–122	4	He did not carry out self-care tasks
18	Sun	153–156	4	He did not carry out self-care tasks
19	Sun	241–246	6	He had a shorter dinner

Table 6
Confusion matrices.

(a) CPS			(b) n-Core			(c) REALTrac					
		Prediction				Prediction		Prediction			
		P'	N'			P'	N'	P'	N'		
Actual	P	216 (TP)	62 (FN)	Actual	P	221 (TP)	57 (FN)	Actual	P	221 (TP)	57 (FN)
	N	99 (FP)	1445 (TN)		N	114 (FP)	1430 (TN)		N	134 (FP)	1410 (TN)

on specific behavioral deviations. Indeed, disease cases are usually rare, and then the use of them for training would cause over fitting. Although we tested the system on a specific disease, the behavioral deviations simulated can occur in many diseases. It is worth noting that the anomaly is not detected via the output of the activation function: it is assessed via the Daily Positive Rate, an anomaly score combining many activation events, which is discussed in the next subsection.

5.2. System assessment

The goal of this section is to measure a match between the behavioral deviations annotated by the human observer in Table 5 and the correspondent results provided by the system. For this purpose, each output sample was considered as a point belonging to one of two classes: Positive (P , i.e., behavioral deviation) and Negative (N , i.e., no deviation). Considering only the period when the patient was at home, the total number of available samples in the experimentation week was 1822, of which 1544 were negative samples and only 278 were positive samples. Class unbalancing is common in the AAL domain, because behavioral deviations must be discovered at the early stage, i.e., when there are few symptoms. Table 6 shows the confusion matrices generated by using the three localization systems. Here, each column counts the instances in a predicted class (i.e., P' and N'), while each row represents the instances in an actual class (i.e., N and P). Thus, the diagonal cells (gray) count the number of correct classifications made for each class, and the off-diagonal cells (white) count the errors made. The former are called True Positives (TP) and True Negatives (TN), whereas the latter False Positives (FP) and False Negatives (FN), considering correct predictions as true, and wrong predictions as false.

Table 7 shows the most important offline assessment indicators of the system. More specifically, *accuracy* is the classification rate, i.e., the number of correctly classified samples with respect to the total number of samples. This indicator is often high when dealing with a small (positive) class against a large (negative) class, because the latter dominates the ratio despite of the results on the positive class. Two better indicators are *precision* and *recall*, meaning the number of behavioral deviations correctly returned, with respect to the total returned and to the total actually occurred, respectively. As both indicators are important, in Table 7 a combination of them, called *F-measure*, is also reported. It is worth noting that the system assessment is very insensitive to the different levels of noise (localization error) coming from the different localization systems.

Table 8 shows true positive, false positive, and the positive rate as an online assessment indicator, averaged per day of a week. Again, the result obtained is very insensitive to the different levels of noise coming from the different localization

Table 7
Offline assessment indicators.

	Accuracy $\frac{TP+TN}{TP+FP+TN+FN}$	Precision $\frac{TP}{TP+FP}$	Recall $\frac{TP}{TP+FN}$	F-measure $\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$
CPS	0.912	0.686	0.777	0.728
n-Core	0.906	0.660	0.795	0.721
REALTrac	0.895	0.623	0.795	0.698

Table 8
Online assessment indicators.

Day	Positive rate = $\frac{TP+FP}{TP+FP+TN+FN}$								
	CPS			n-Core			REALTrac		
	TP	FP	Positive rate	TP	FP	Positive rate	TP	FP	Positive rate
Mon	0	2	0.008	0	3	0.012	0	9	0.036
Tue	15	15	0.115	15	20	0.134	14	21	0.134
Wed	46	9	0.191	47	9	0.194	46	11	0.198
Thu	52	7	0.242	53	10	0.258	52	13	0.266
Fri	34	28	0.215	35	30	0.226	39	34	0.254
Sat	53	8	0.212	54	9	0.219	53	11	0.222
Sun	16	30	0.228	17	33	0.248	17	35	0.257

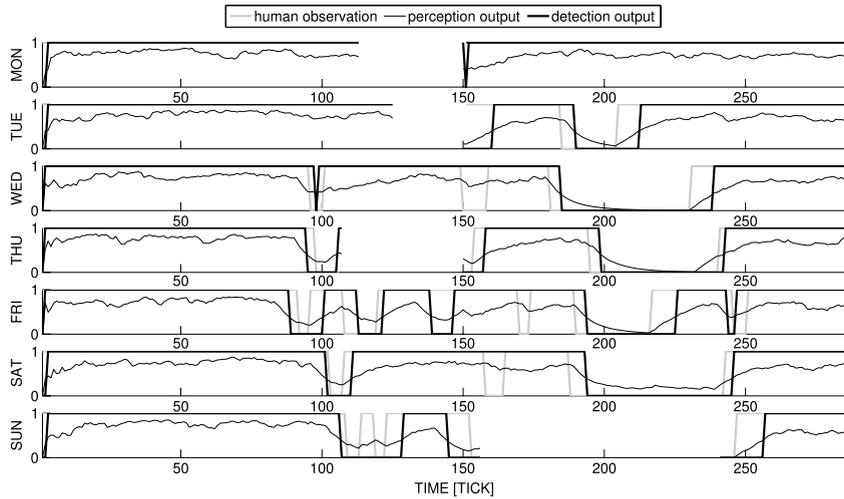


Fig. 13. Outputs of the perception, detection, and of the human observation when the error model of the CPS localization system is applied on each day of the observed week.

systems, and consistent with what is shown in Table 7. Indeed, starting from Monday, the number and the duration of the behavioral deviations observed in the testing session are increasing up to Sunday.

In order to directly assess how the output of the system was computed during the testing session, Figs. 13, 14, and 15 show the outputs of the perception (analogical black signal), the detection (digital black signal), and the human observation (digital gray signal), when the error model of the analyzed localization systems is applied on each day of the week. Here, it is possible to realize that the system manifests an “inertial” character: chains of behavioral deviation events are better recognized than isolated ones. This is consistent with the memory effect of the marking process. Moreover, it is possible to realize that events shorter than the event duration considered in the tuning stage are more difficult to be recognized. Actually this is not a problem: for a given localization system, different duration events may be recognized by different instances of the monitoring system with different parameters tuning.

Marking is a general purpose data processing mechanism that may fit phenomena of different sizes and nature such as: fluctuations of a localization system, transitions between points of interest of an apartment, human mobility patterns, human diseases patterns, and so on. This paper focuses on the application of stigmergy to behavioral dynamics in indoor mobility generated by human diseases. For this purpose, the design is not specialized to fit the error of a specific localization system. By experimenting that the used approach is not sensitive with respect to benchmark localization systems, we obtain that localization error is naturally compensated. Similarly, the design of the marking process is not specialized to fit the structure of the apartment: having marks large enough to distinguish the closest point of interests it is sufficient for our purposes. Different stigmergic layers may be designed for each (sub-)dynamics. However, this would lead to an expensive,

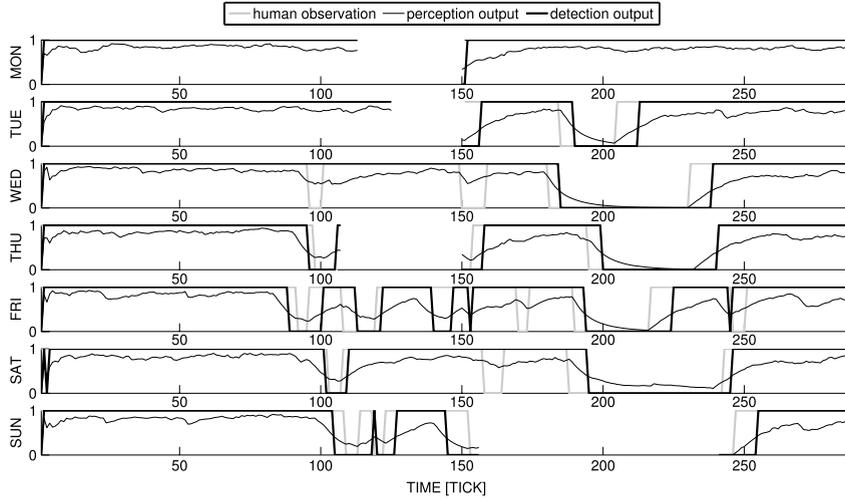


Fig. 14. Outputs of the perception, detection, and of the human observation when the error model of the n-Core localization system is applied on each day of the observed week.

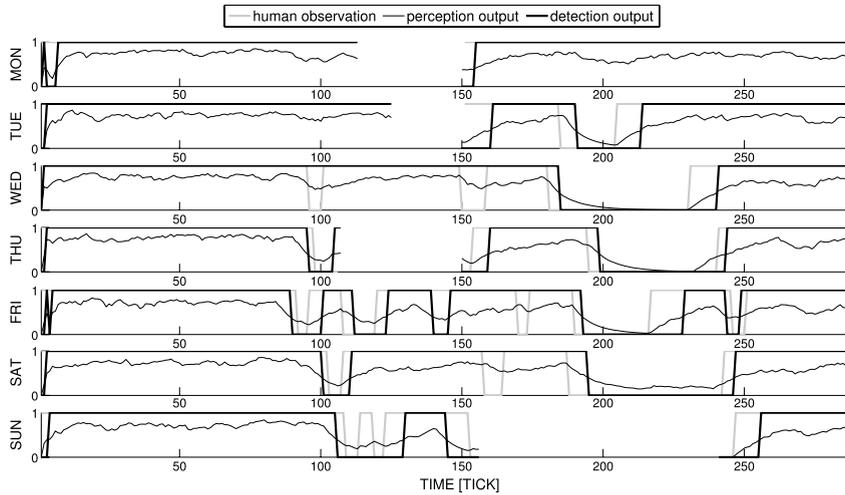


Fig. 15. Outputs of the perception, detection, and of the human observation when the error model of the REALTrac localization system is applied on each day of the observed week.

reductionist and cognitivist design. For this reason, in this paper the stigmergic processing is focused on human mobility patterns, showing that the approach is intrinsically able to tackle other kinds of uncertainty.

Currently, we are designing and developing an adaptive scheme in the marking process and the detection process, in contrast with the current adaptable scheme. More specifically, one of the problems to solve when optimizing parameters is that optimization encompasses all available scenarios at once and concerns the tuning of all parameters over the overall training set, which should be spread across the entire space of diseases. This optimization scheme is usually referred to as global tuning, and leads to increasing difficulties from the practical perspective, due to fitting different scaled spatiotemporal behavioral deviations. An alternative is local modeling. For example, the design paradigm of the *receptive fields* is based on local tuning, i.e., on sub-models that focus predominantly on some selected regions of the entire diseases domain. An overall model is then formed by combining such local models. This modular layer may provide a topology offering a considerable level of flexibility, as the resulting receptive fields can be highly diversified according to the distribution of the different behavioral deviations [47].

6. Conclusions and future work

In this paper we presented a novel approach for monitoring elderly behavior, by focusing on diseases events. In contrast with the literature in the field, our approach does not require explicit modeling of activities of daily living since it is based on the emergent paradigm. We have shown how localization systems with different error models can be used for this purpose.

Moreover, we have discussed and analyzed a real-world case of application, discovering the most interesting properties of the approach. Finally, we discussed a possible future development of the system.

Future work will be oriented at implementing a system based on the presented concepts, starting with the simple case of a basic domotic environment (where light switches, an intrusion detection system, and, possibly, home appliances generate events on a domotic home network) used as a basic source of indoor positioning information. One possibility is to test the concept on more extensive real data gathered from real test sites provided by the EU FP7 GiraffPlus project² and other living labs from the EU FP7 DOREMI project.³

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References

- [1] U. Nations, *World Population Ageing*, 2013, UNITED NATIONS PUBN, 2014.
- [2] T. Kleinberger, M. Becker, E. Ras, A. Holzinger, P. Müller, *Ambient intelligence in assisted living: enable elderly people to handle future interfaces*, in: *Universal Access in Human-Computer Interaction*. Ambient Interaction, Springer, 2007, pp. 103–112.
- [3] F. Palumbo, J. Ullberg, A. Štimec, F. Furfari, L. Karlsson, S. Coradeschi, *Sensor network infrastructure for a home care monitoring system*, *Sensors* 14 (3) (2014) 3833–3860.
- [4] S. Chernbumroong, S. Cang, A. Atkins, H. Yu, *Elderly activities recognition and classification for applications in assisted living*, *Expert Syst. Appl.* 40 (5) (2013) 1662–1674.
- [5] J.A. Botia, A. Villa, J. Palma, *Ambient assisted living system for in-home monitoring of healthy independent elders*, *Expert Syst. Appl.* 39 (9) (2012) 8136–8148.
- [6] H. Storf, T. Kleinberger, M. Becker, M. Schmitt, F. Bomarius, S. Prueckner, *An Event-Driven Approach to Activity Recognition in Ambient Assisted Living*, Springer, 2009.
- [7] C. Anagnostopoulos, S. Hadjiefthymiades, *Advanced fuzzy inference engines in situation aware computing*, *Fuzzy Sets and Systems* 161 (4) (2010) 498–521.
- [8] M.G. Cimino, B. Lazzarini, F. Marcelloni, A. Ciaramella, *An adaptive rule-based approach for managing situation-awareness*, *Expert Syst. Appl.* 39 (12) (2012) 10796–10811.
- [9] P. Rashidi, A. Mihailidis, *A survey on ambient-assisted living tools for older adults*, *IEEE J. Biomed. Health Inform.* 17 (3) (2013) 579–590.
- [10] H. Storf, M. Becker, M. Riedl, *Rule-based activity recognition framework: Challenges, technique and learning*, in: *Pervasive Computing Technologies for Healthcare*, 2009. PervasiveHealth 2009. 3rd International Conference on, IEEE, 2009, pp. 1–7.
- [11] L. Chen, C. Nugent, *Ontology-based activity recognition in intelligent pervasive environments*, *Int. J. Web Inf. Syst.* 5 (4) (2009) 410–430.
- [12] L. Chen, I. Khalil, *Activity recognition: Approaches, practices and trends*, in: *Activity Recognition in Pervasive Intelligent Environments*, Springer, 2011, pp. 1–31.
- [13] H. Liu, H. Darabi, P. Banerjee, J. Liu, *Survey of wireless indoor positioning techniques and systems*, *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* 37 (6) (2007) 1067–1080.
- [14] F. Palumbo, P. Barsocchi, *SALT: Source-agnostic localization technique based on context data from binary sensor networks*, in: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, LNCS, vol. 8850, 2014, pp. 17–32.
- [15] D. Vernon, G. Metta, G. Sandini, *A survey of artificial cognitive systems: Implications for the autonomous development of mental capabilities in computational agents*, *IEEE Trans. Evol. Comput.* 11 (2) (2007) 151–180.
- [16] P. Barron, V. Cahill, *Using stigmergy to co-ordinate pervasive computing environments*, in: *Mobile Computing Systems and Applications*, 2004. WMCSA 2004. Sixth IEEE Workshop on, IEEE, 2004, pp. 62–71.
- [17] M.G. Cimino, F. Marcelloni, *Autonomic tracing of production processes with mobile and agent-based computing*, *Inform. Sci.* 181 (5) (2011) 935–953.
- [18] S.-y. Sato, T. Nakamura, Y. Sato, *Behavior-based stigmergic navigation*, in: *Proceedings of the 12th ACM International Conference Adjunct Papers on Ubiquitous Computing-Adjunct*, ACM, 2010, pp. 429–430.
- [19] D.J. Cook, J.C. Augusto, V.R. Jakkula, *Ambient intelligence: Technologies, applications, and opportunities*, *Pervasive Mob. Comput.* 5 (4) (2009) 277–298.
- [20] L. Atallah, G.-Z. Yang, *The use of pervasive sensing for behaviour profiling—a survey*, *Pervasive Mob. Comput.* 5 (5) (2009) 447–464.
- [21] N.D. Rodríguez, M.P. Cuéllar, J. Lilius, M.D. Calvo-Flores, *A survey on ontologies for human behavior recognition*, *ACM Comput. Surv. (CSUR)* 46 (4) (2014) 43.
- [22] J. Ye, S. Dobson, S. McKeever, *Situation identification techniques in pervasive computing: A review*, *Pervasive Mob. Comput.* 8 (1) (2012) 36–66.
- [23] E.M. Tapia, S.S. Intille, K. Larson, *Activity Recognition in the Home Using Simple and Ubiquitous Sensors*, Springer, 2004.
- [24] D.J. Patterson, L. Liao, D. Fox, H. Kautz, *Inferring high-level behavior from low-level sensors*, in: *UbiComp 2003: Ubiquitous Computing*, Springer, 2003, pp. 73–89.
- [25] R. Hamid, S. Maddi, A. Johnson, A. Bobick, I. Essa, C. Isbell, *A novel sequence representation for unsupervised analysis of human activities*, *Artificial Intelligence* 173 (14) (2009) 1221–1244.
- [26] O. Brdiczka, J.L. Crowley, P. Reignier, *Learning situation models in a smart home*, *IEEE Trans. Syst. Man Cybern. B* 39 (1) (2009) 56–63.
- [27] U. Maurer, A. Smailagic, D.P. Siewiorek, M. Deisher, *Activity recognition and monitoring using multiple sensors on different body positions*, in: *Wearable and Implantable Body Sensor Networks*, 2006. BSN 2006. International Workshop on, IEEE, 2006, p. 4.
- [28] M. Delgado, M. Ros, M. Amparo Vila, *Correct behavior identification system in a tagged world*, *Expert Syst. Appl.* 36 (6) (2009) 9899–9906.
- [29] L.L. Chen, J. Biswas, *Tutorial: an introduction to ontology-based activity recognition*, in: *Proceedings of the 7th International Conference on Mobile Computing and Multimedia, MoMM2009*, Kuala Lumpur, Malaysia, 2009, pp. 14–16.
- [30] A. Yamaguchi, M. Ogawa, T. Tamura, T. Togawa, *Monitoring behavior in the home using positioning sensors*, in: *Engineering in Medicine and Biology Society*, 1998. *Proceedings of the 20th Annual International Conference of the IEEE*, Vol. 4, IEEE, 1998, pp. 1977–1979.
- [31] N. Noury, T. Hervé, V. Rialle, G. Viron, E. Mercier, G. Morey, A. Moro, T. Porcheron, *Monitoring behavior in home using a smart fall sensor and position sensors*, in: *Microtechnologies in Medicine and Biology*, 1st Annual International, Conference on, 2000, IEEE, 2000, pp. 607–610.
- [32] G.P. Joshi, S. Acharya, C.-S. Kim, B.-S. Kim, S.W. Kim, *Smart solutions in elderly care facilities with RFID system and its integration with wireless sensor networks*, *Int. J. Distrib. Sens. Netw.* (2014).

² <http://giraffplus.eu/>.

³ <http://doremi-fp7.eu/>.

- [33] J. Kropf, L. Roedl, A. Hochgatterer, A modular and flexible system for activity recognition and smart home control based on nonobtrusive sensors, in: *Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, 2012 6th International Conference on, IEEE, 2012, pp. 245–251.
- [34] K. Rieping, G. Englebienne, B. Kröse, Behavior analysis of elderly using topic models, *Pervasive Mob. Comput.* 15 (2014) 181–199.
- [35] G. Virone, Assessing everyday life behavioral rhythms for the older generation, *Pervasive Mob. Comput.* 5 (5) (2009) 606–622.
- [36] S. Lühr, G. West, S. Venkatesh, Recognition of emergent human behaviour in a smart home: A data mining approach, *Pervasive Mob. Comput.* 3 (2) (2007) 95–116.
- [37] P. Barsocchi, S. Chessa, F. Furfari, F. Potorti, Evaluating ambient assisted living solutions: The localization competition, *IEEE Pervasive Comput.* 12 (4) (2013) 72–79.
- [38] J.A. Álvarez-García, P. Barsocchi, S. Chessa, D. Salvi, Evaluation of localization and activity recognition systems for ambient assisted living: The experience of the 2012 eval competition, *J. Ambient Intell. Smart Environ.* 5 (1) (2013) 119–132.
- [39] M. Bocca, O. Kaltiokallio, N. Patwari, Radio tomographic imaging for ambient assisted living, in: *Evaluating AAL Systems Through Competitive Benchmarking*, Springer, 2013, pp. 108–130.
- [40] D.I. Tapia, Ó. García, R.S. Alonso, F. Guevara, J. Catalina, R.A. Bravo, J.M. Corchado, The n-core polaris real-time locating system at the eval competition, in: *Evaluating AAL Systems Through Competitive Benchmarking. Indoor Localization and Tracking*, Springer, 2012, pp. 92–106.
- [41] A. Moschevikin, A. Galov, A. Soloviev, A. Mikov, A. Volkov, S. Reginya, Realtrac technology overview, in: *Evaluating AAL Systems Through Competitive Benchmarking*, Springer, 2013, pp. 60–71.
- [42] M. Tan, H.-B. Fang, G.-L. Tian, G. Wei, Testing multivariate normality in incomplete data of small sample size, *J. Multivariate Anal.* 93 (1) (2005) 164–179.
- [43] K.V. Mardia, Applications of some measures of multivariate skewness and kurtosis in testing normality and robustness studies, *Sankhyā Ser. B* (1974) 115–128.
- [44] G. Fasano, A. Franceschini, A multidimensional version of the Kolmogorov–Smirnov test, *Mon. Not. R. Astron. Soc.* 225 (1) (1987) 155–170.
- [45] J.A. Doornik, H. Hansen, An omnibus test for univariate and multivariate normality*, *Oxford Bull. Econ. Stat.* 70 (s1) (2008) 927–939.
- [46] M. Avvenuti, D. Cesarini, M.G. Cimino, MARS, a multi-agent system for assessing rowers' coordination via motion-based stigmergy, *Sensors* 13 (9) (2013) 12218–12243.
- [47] M.G. Cimino, W. Pedrycz, B. Lazzerini, F. Marcelloni, Using multilayer perceptrons as receptive fields in the design of neural networks, *Neurocomputing* 72 (10) (2009) 2536–2548.