Stigmergy-based Long-Term Monitoring of Indoor Users Mobility in Ambient Assisted Living Environments: the DOREMI Project Approach

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Abstract. Aging trends in Europe motivate the need for technological solutions aimed at preventing the main causes of morbidity and premature mortality. In this framework, the DOREMI project addresses three important causes of morbidity and mortality in the elderly by devising an ICT-based home care services for aging people to contrast cognitive decline, sedentariness and unhealthy dietary habits. In DOREMI, the house itself is transformed in an unobtrusive monitoring environment able to keep track of the daily activities of older users. In this paper, we present a system able to detect behavioral deviations of the routine indoor activities, in terms of indoor movements, on the basis of indoor localization information coming from the deployed environmental sensor network and a swarm intelligence method, namely stigmergy. Similarity evaluation is performed between stigmergic maps over different weeks in order to assess deviations. These deviations can be related to an effective application of the DOREMI protocol as well as to malfunctioning devices, thus representing a useful tool to detect changes in the DOREMI environment and in the user's life-style.
The proposed solution has been validated in a pilot study lasted six months and carried out in UK and in Italy.

Keywords: Stigmergy, Long-term Monitoring, Ambient Assisted Living

1 Introduction

Due to advancements in the medical therapies and to different styles of life, all countries in Europe are experiencing an aging of their populations, with a decrease in the number of people retiring. Health trends among the elderly are mixed: severe disability is declining in some countries but increasing in others, while mild disability and chronic disease are generally increasing. As a consequence, long-term care costs are certain to increase with the aging of the population unless appropriate measures are implemented in time. Population aging will not inevitably lead to significantly higher health care expenditure, if appropriate actions are implemented and elderly people are empowered to follow them. According to the World Health Organization (WHO) recommendations [1], these actions include: i) reducing the risk of disease and promoting the maintenance of functions, ii) incrementing physical exercises and social participation, iii) developing adequate systems of long-term care, iv) supporting economic and social integration.

According to the University College of Dublin Institute of Food and Health Policy Seminar Series, three are the most notable health promotion and disease prevention programs that target the main causes of morbidity and premature mortality: obesity, hypertension, and mental disorders. These programs address malnutrition, sedentariness, and cognitive decline, as they are identified as the main conditions affecting the quality of life of elderly people and driving to the above-indicated diseases.

These three factors represent the target areas of improvement treated in the DOREMI project [1], whose vision aimed at developing a systemic solution for healthy aging, based on a well targeted problem definition and model, able to prolong the functional and cognitive capacity of the elderly by empowering, stimulating and unobtrusively monitoring the daily activities according to well defined "Active Aging" lifestyle protocols [2]. The project is characterized by a unified vision of being elderly today by a constructive interaction among mind, body, and social engagement. The subject with cognitive decline is prone to increase malnutrition and sedentariness habits; in this condition, an integrated control of psychologically related socio-physical disabilities, vital signs combined with nutritional behavior, physical activity and social interaction may represent a preventive approach towards further deterioration of the cognitive decline and onset of new clinical manifestations

Sedentariness, i.e., inappropriate mobilization, is responsible for high incidence of household falls and injuries, which happen to one third of people over 60 years, with a consequent disability as well as physical and psychological repercussions that accelerate a physiological and functional decline. This loop can induce a state of depression or social isolation, to which a cognitive decline is often associated. During the aging process, all humans develop some degree of cognitive decline; this natural decline can be accelerated by illnesses, psychological and social factors and so on, and it is responsible of social isolation. On the other hand, isolation can have a negative effect on nutrition, as eating is a social event. Physical activity is a key component of healthy lifestyles; in [3], the authors compare by sex, physical activity, and academic qualifications the symptomatology of depression among elders, identifying a significant correlation among physical activity, depression and anxiety.

In DOREMI, the house itself is transformed in an unobtrusive monitoring environment able to keep track of the daily activities of the elderly people at risk of malnutrition, sedentariness and cognitive decline; a gamified environment was developed to engage the elderly and to stimulate their social interaction

[1] http://www.doremi-fp7.eu/

and physical activity; the only wearable object is a simple bracelet with special functions for elderly.

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 from the routine in indoor activities, in terms of movements, on the basis of indoor localization information coming from the deployed environmental sensor network and a swarm intelligence method, namely stigmergy. More specifically, spatio-temporal tracks provided by the activations of the environmental sensors are augmented, via marker-based stigmergy, in order to enable their self-organization. This allows a marking structure spontaneously appearing and staying at runtime, when some local dynamism occurs. Similarity evaluation is performed between stigmergic maps over different weeks in order to assess deviations. These deviations can be related to an effective application of the DOREMI protocol as well as to malfunctioning devices representing a useful tool to detect changes in the DOREMI environment and in the user's life-style.

The proposed solution has been validated in a pilot study lasted six months and carried out in UK and in Italy.

The paper is organized as follows. Section 2 presents other correlated projects and highlights the aspects characterizing DOREMI. Section 3 describes the overall DOREMI system deployed at user's house. Section 4 describes the proposed long-term monitoring system and, in Section 5, how it is able to detect the impact of the DOREMI protocol on the user's life-style. Section 6 draws the conclusions.

2 Related Initiatives for Ambient Assisted Living

As identified in the most recent global trends survey (Aging In Place Technology Watch [4]), the technologies for active aging can be categorized in four areas: safety & secure; health & wellness; communication & engagement; learning & contributing. Considering the level of EU technology maturity in this sector, it is noteworthy to highlight that in the last decade a number of scientific research and deployment projects addressing the technologies for active and independent living have been developed by transnational consortia, significantly contributing to learning and development in the field of ICT solutions and services for elderly people. The 7th Framework Programme (FP7), the Competitiveness and Innovation Framework Programme (CIP), and the Ambient Assisted Living (AAL) Joint programme are the funding programmes most exploited at EU level in order to develop and test innovative technologies in the area of independent living.

The following list reports the acronym of the most known and successful projects, fitting into the four specific categories above mentioned, for each programme:

- **FP7**: universAAL [5], OASIS [6], AALIANCE [7], BRAID [8], GiraffPlus [9];

– **CIP-ICT**: COMMONWELL [2], DREAMING [3], ISISEMD [4], Long Lasting Memories [5], SOCIABLE [6], T-SENIORITY [7], CLEAR [8], NEXES [9], HOME SWEET HOME [10];
– **AAL**:
  • ICT-based solutions for prevention and management of chronic conditions: Agnes [11], Amica [12], eCAALYX [13];
  • ICT-based solutions for advancement of social Interaction: Join-In [14], Hopes [15], Silver Game [16].

Each of the listed projects addresses specific problems in the different technology areas, such as monitoring systems, tele-health, online social networks, etc; however, all these projects present as a major drawback the lack of a systemic approach in both clinical and technological areas, as well as the lack of a sustainable model able to guarantee the cost effectiveness of the proposed technologies and services and their wide diffusion.

In general, we can say that all the technologies and services addressed by the mentioned projects were specifically devised to support elderly people in the management of chronic diseases and co-morbidities in the most common disease areas of cardiovascular, neuro-degenerative (e.g., Parkinson, Alzheimer, Dementia) and COPD diseases. Nevertheless, they do not holistically consider the psychological, social and physical aspects as a whole. The monitoring systems developed and implemented in the projects, both for personal and environmental data collection, mainly addressed home-based scenarios only. The outdoor environment has been mainly investigated by using the location-based services nowadays available with mobile smart phones but without posing the right attention to the power consumption. In many cases, monitoring activities were supported by wearable garment or smart t-shirts equipped with a network of sensors able to collect and transfer only physio-pathological parameters (e.g., cardio or respiratory data) without taking into consideration the overall daily behavioral aspects affecting the elderly health-care. Research aiming at recognizing the daily activities of people has steadily progressed, but little focus has

[2] http://commonwell.eu/
[3] http://www.dreaming-project.org/
[4] http://www.isisemd.eu/
[5] http://www.longlastingmemories.eu/
[6] http://www.sociable-project.eu/
[7] http://tseniority.idieikon.com/
[8] http://www.habiliseurope.eu/?q=node/5
[9] http://www.nexeshealth.eu/
[10] http://www.homesweethome-project.be/
[11] http://www.aal-europe.eu/projects/agnes/
[12] http://www.aal-europe.eu/projects/amica/
[13] http://www.aal-europe.eu/projects/ecaalyx/
[14] http://www.aal-europe.eu/projects/join-in/
[15] http://www.aal-europe.eu/projects/hopes/
[16] http://www.aal-europe.eu/projects/silver-game/

been devoted to recognizing jointly activities as well as movements in a specific activity and users context.

In the area of cognitive stimulation and monitoring, further than the above mentioned limitation due to the target on chronic conditions (e.g., Alzheimer, Parkinson, etc.), the adopted solutions (e.g., games, social networks, interactive questionnaires, etc.) mainly focused on the cognitive decline assessment without considering the monitoring of relevant complementary impact factors such as the combination with physical activity and social interaction. Cognitive decline may negatively interact with relevant functions of cardiovascular system, through impairment of vascular endothelial function favored by sedentariness. Stimulation of physical activity may prevent or slowdown the deterioration of vascular and cognitive functions, as well.

As far as the physical activity stimulation and monitoring is concerned, it is noteworthy to underline that most of the projects targeting this problem mainly focused on the implementation of home-based "wii-fit like" rehabilitation exergames stimulating the target user through virtual exercising and monitoring the performance in front of a PC. However, the physiological stimulus to preserve efficiency is a continuous, daily activity carried out both indoor and outdoor.

In the area of social interaction, some projects addressed the development of a virtual world where: the elderly establish social relationships; robot systems interact with older users; interactive TV and video conferencing; etc. This is done, in order to encourage better dialog among people and social networks concerning the same disease experience. However, despite the recognized importance of the technology to support the social interaction, none of the projects so far analyzed set up a systemic solution combining social engagement, stimulation systems and interaction monitoring systems, able to track the level of social interaction and analyze, through a behavioral analysis approach, how social network interaction can stimulate the real life social interaction as an important factor for well-being.

DOREMI approached the problem by combining all the aspects together and developing a systemic solution.

3 The DOREMI Monitoring Environment

The DOREMI monitoring environment is constituted by a Wireless Sensor Network (WSN) formed by a set of heterogeneous devices for retrieving data from users to measure the following Key Performance Indicators (KPI): physical activity, vital parameters, and social interactions. By the correct measurement of these indicators, the whole DOREMI system gets feedback about the performance of the gamified environment, physical exercises and, in general, all the actions performed by the user. The DOREMI system consists of the combination of several technologies and subsystems to enable the monitoring of the following parameters: step counting, indoor location (at room level), physical movements, interactions with people, outdoor location, heart rate, weight, and balance. Table 1 relates the KPIs with the type of sensor used.

Table 1: KPI identified in the active aging life-style protocol and how they relate with the type of sensor used

KPI Type	KPI	Data	Device
Clinical	Vital Parameters	Weight	Balance Board
		Balance	
		Heart Rate	DOREMI Wristband
	Physical Activity	Wrist Acceleration	
		Number of Steps	
		Indoor Position	
		Sensors Activations	Environmental WSN
Social	Number of Interactions		
		GPS	Smartphone

User monitoring takes place both at home and outdoor. The sensor network has been consequently designed to follow the users during their daily life acquiring suitable information unobtrusively. The overall DOREMI deployment diagram is shown in Figure 1.

All data generated in the WSN are sent to the middleware [10–12], an end-to-end communication system that enables secure transmission and retention of sensors data. It also stores data in the sensor database through a data recorder module. The data collected by the WSN pertain to: weight and balance (smart balance), indoor activity (PIR and Door Contact sensors), heartbeat and body movements (wearable wristband), Indoor Location (Indoor Location System and Wristband), outdoor Location (wristband and smartphone with GPS). To collect these data, the WSN leverages both the devices installed in the apartment of the DOREMI user (i.e., the environmental sensors, the networking and the computing facilities) and the personal devices that are mainly used outdoor (i.e., the wearable sensor and the mobile phone).

The environmental sensors are intended to get suitable data from the daily life of the user to evaluate the social interactions in an unobtrusive, user-unaware way. These sensors are called "environmental" since they are installed in the rooms of the user's house and do not require any user intervention, thus not interfering in his daily life. DOREMI uses two types of environmental sensors: presence detectors, based on passive infrared technology (PIR), and door detectors, based on magnetic contacts. Measurement from these two kinds of devices are combined to assess, among others, the number of social interactions at home and an approximation to the number of people interacting [13]. The selection of the sensors, as the rest of the subsystems, has been performed considering requirements from the lifestyle protocol, the smart environment, and the WSN. The devices used in DOREMI are commercial products of the Z-Wave catalog. This technology has been selected due to its maturity and wide availability of devices, accomplishing the requirements for the project (API to access the full data, low energy consumption, wireless, and ease of deployment). The Z-Wave

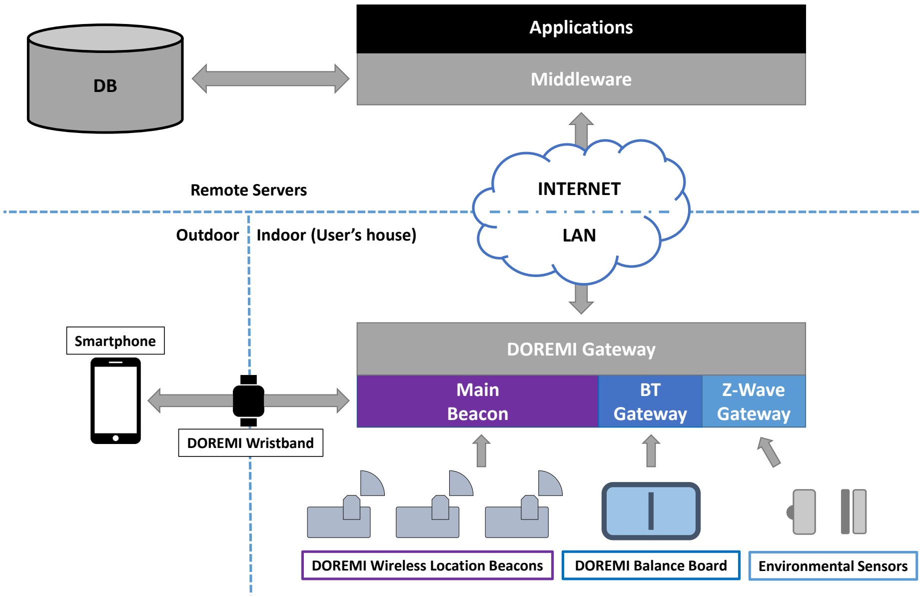


Fig. 1: DOREMI deployment diagram

technology requires an additional element to set up and manage the network and to retrieve all the data generated by each Z-Wave sensor. In DOREMI, this element is also responsible to offer data access to a middleware integration layer running on the DOREMI Gateway; a commercial Z-Wave gateway has been selected to perform this task.

4 Long-Term Monitoring of the Indoor User's Routine

Besides the supervised activity recognition modules available in DOREMI (they focus on short-term activities, like BERG score estimation [14] and human daily movements [15] related to caloric expenditure), one of the main aim of the DOREMI project is to monitor the user over the long period in order to infer his indoor behavioral changes potentially connected to better conditions in terms of sedentariness, socialization, and physiological data. For this reason, we started analyzing the environmental sensors deployed in the test sites and applying the stigmergic technique proposed in [16–18]. As input, we have the maps of the users' houses, the coordinates of the sensors in the houses, and the relative activations with timestamps. In previous works [19, 20], we showed that these simple binary information (e.g., door open/close, presence detected/not detected, etc.) coming from environmental sensors are useful to build an effective low-resolution indoor localization system. In this Section, we describe how this kind of information is used to build a long-term monitoring system.

4.1 Stigmergic Maps

From the retrieved sensors' coordinates, we build the stigmergic map used by the proposed algorithm, where the deployed environmental sensors act as agents. Stigmergy [21, 22] is a mechanism of spontaneous, indirect coordination between agents, where the trace left in the environment by an action stimulates the performance of a subsequent action, by the same or a different agent. The word Stigmergy is derived from the Greek words *stigma* (sign) and *ergon* (work/action), capturing the notion that an agent's action leaves signs in the environment that the agent itself and other agents sense and that determine and incite their subsequent actions. It is a form of self-organization that produces complex, apparently intelligent structures, without the need for any planning, control, or even communication among the agents. It was first observed in social insects: ants for example exchange information by laying down pheromones on their way back to the nest when they have found food. In this way, they collectively develop a complex network of trails, connecting the nest in the most efficient way to the different food sources.

In our scenario, the sensors (as agents) leave marks in the environment creating a virtual pheromone map (the stigmergic map) that can be used to infer emergent aspects. Our purpose is to connect these emergent changes to the behavior of the user living in the environment.

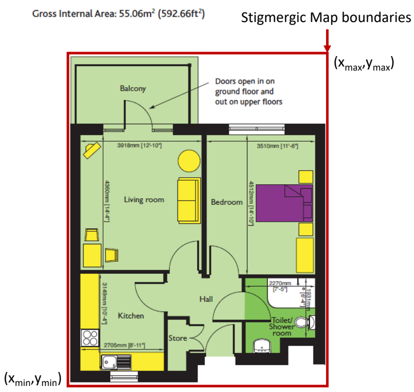


Fig. 2: The boundaries of the stigmergic map for a typical one bedroom apartment

The first step is to calculate the boundaries of our stigmergic map using the coordinates of all the angles of the rooms. Figure 2 shows the boundaries of the stigmergic map for a typical one-bedroom apartment, where (x_{min}, y_{min}) and (x_{max}, y_{max}) are the closest and the farthest coordinates in the rooms configuration file, respectively (containing the coordinates of all the rooms). The available sensors are: motion detectors in the living room, bedroom, and kitchen and the door contact placed on the main entrance.

For each apartment, we update the stigmergic map every 10 minutes. During this period, we release a pheromone mark on the map in correspondence of the coordinates of a sensor, if activated. As a result, we obtain for each day 144 images representing the stigmergic maps at each time step.

The update process of the stigmergic map is based on the potential field model [23]. At each time step, it computes the intensity at distance d_k from each pheromone k using equation 1:

$$p(d_k) = \begin{cases} p_k \left(1 - \frac{d_k}{\sigma}\right) & \text{if } 0 < d_k < \sigma \\ 0 & \text{if } d_k \geq \sigma \end{cases} \tag{1}$$

where $p(d_k)$ is the intensity of pheromone k at distance d_k due to diffusion, σ is the sensitivity range, and p_k is the actual intensity of pheromone k. Due to the stigmergic aggregation of all the N sources located within σ, the resulting pheromone intensity sensed in an arbitrary location is given by equation 2:

$$P = \sum_{k=1}^{N} p_k \left(1 - \frac{d_k}{\sigma}\right). \tag{2}$$

Assuming that the evaporation effect linearly decreases the pheromone intensity, it is possible to update the resulting pheromone at time t, as shown in equation 3:

$$P = \sum_{k=1}^{N} p_k \left(1 - \frac{d_k}{\sigma}\right)\left(1 - \frac{t - t_k}{\tau}\right) \tag{3}$$

where t_k is the time of creation of the pheromone k and τ is the evaporation parameter. In our analysis, we chose as initial intensity $p_k = 1$, as sensitivity range $\sigma = 2m$, and as evaporation $\tau = 2min$ (where $t - t_k = 10min$).

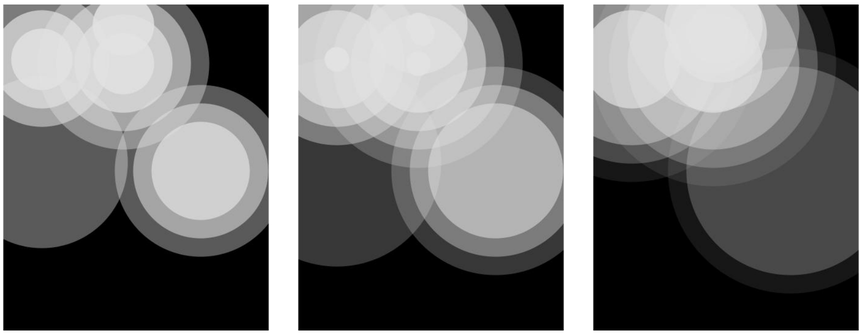
Figure 3 shows three frames extracted from a sample day of usage of the DOREMI system in a flat. It can be seen how pheromone marks diffuse, evaporate, and aggregate among them.

4.2 Structural Similarity and Local Maxima

In order to calculate similarities between weeks of intervention, we processed each image pairwise between the same days of different weeks. We used the Structural Similarity ($SSIM$) index described in [24]. It is used for measuring the similarity between two images. The $SSIM$ index is calculated on various windows of an image. The measure between two windows x and y of size $N \times N$ is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{4}$$

where: μ_x and μ_y are the average values of x and y, respectively; σ_x^2 and σ_y^2 are the variance values of x and y, respectively; σ_{xy} is the covariance of x and y;



(a) t_i (b) t_{i+1} (c) t_{i+2}

Fig. 3: Three subsequent frames of the update process of the stigmergic map

$c_1 = (k_1 L)^2$ and $c_2 = (k_2 L)^2$ are two variables to stabilize the division with weak denominator, where L being the dynamic range of the pixel-values (typically this is 2 $\times$ #bits per pixel-1, in our case 264-1); $k_1 = 0.01$ and $K_2 = 0.03$ are set by default. The resultant $SSIM$ index is a decimal value between -1 and 1, where value 1 is only reachable in the case of two identical sets of data. We calculated it on a window sizes of 8x8 (N = 8, corresponding to $0.8m \times 0.8m$ in the real environment). The resulting 144×7 $SSIM$ indexes for each couple of weeks were mediated, obtaining an index for each pair of weeks i and j: S_{ij}. This index was used to measure the degree of change in the behavioral routine of the user, week by week, during the DOREMI intervention.

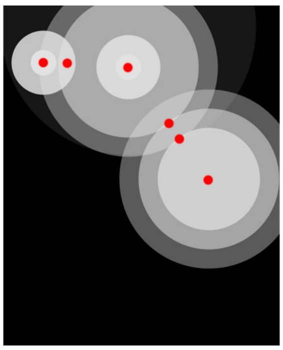


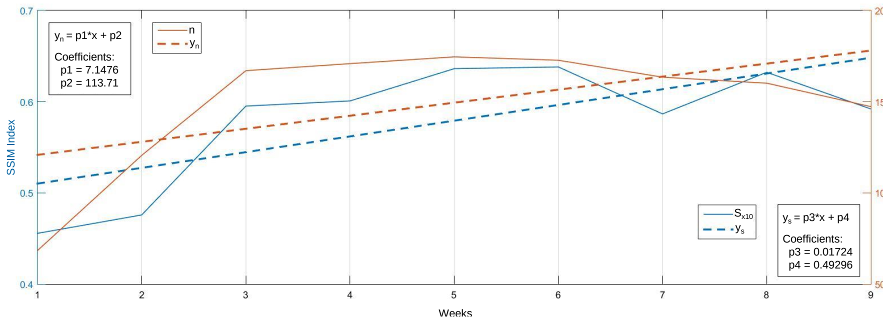
Fig. 4: Local maxima over 10 min of monitoring ($n = 6$ shown as red dots)

Together with the behavioral similarity between weeks, we also wanted to measure how many movements the user was performing during the intervention, in order to correlate the behavioral changes to an actual decrease in the user's sedentariness. For this reason, we calculated the number of local maxima n in the stigmergic map due to aggregation of environmental sensors' activations per day. Figure 4 shows the local maxima n for an image collecting 10 minutes of sensors' activations.

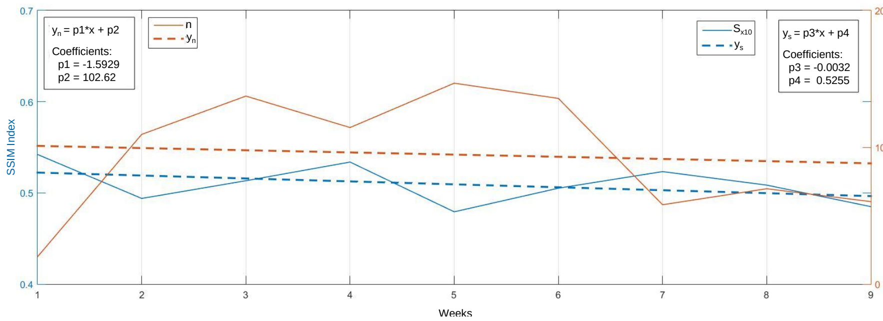
5 Detecting the Impact of the DOREMI Protocol

At the end of the intervention phase of the DOREMI project in UK and IT, we processed, for each of the 15 UK flats (11 flat for the intervention group and 4 for the control group) and the 17 IT flats (14 flats for the intervention group and 3 for the control group), 70 days of stigmergic maps for a total of 10080 images (aggregation of pheromones for each 10 minutes) for each country.

From the measured values of similarity S_{ij} and the number of local maxima n, we exploratory analyzed the period of the DOREMI intervention in the pilot sites in order to find out how the DOREMI protocol impacted on the user indoor mobility.



(a) Intervention Group



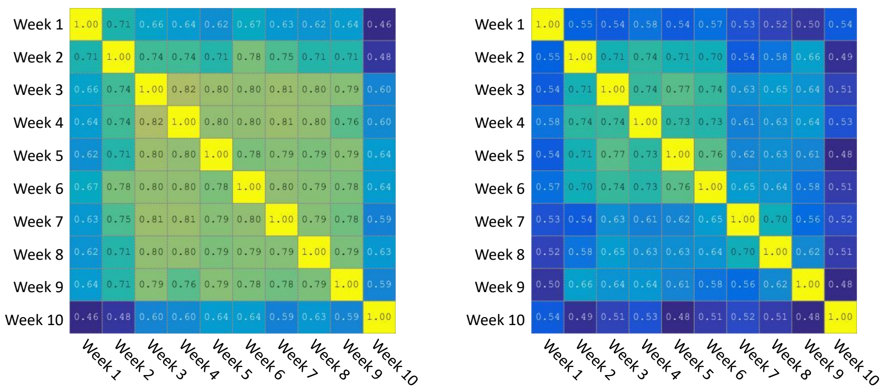
(b) Control Group

Fig. 5: The similarity between week 10 and the other weeks of the DOREMI experimentation (S_{x10}) and the number of local maxima in the stigmergic maps during the weeks of experimentation (n) for an intervention group flat (a) and a control group flat (b).

In the DOREMI experimentation, we have 11 intervention sites and 4 control sites (those who do not use the exer-game mobile application) for the UK pilot and 14 intervention and 3 control sites for the IT pilot. We started correlating the indoor behavioral changes in sedentariness in the intervention and control group flats.

Figure 5 shows the plots of the similarity index S_{x10} and the number of local maxima n during the 10 weeks of pilot for an intervention group flat (a) and a control group flat (b) in UK. S_{x10} represents the similarity between the last (week 10) and the past weeks (x from 1 to 9). We can see that, in a typical intervention group flat, the user slowly changes his behavior in the house: an increasing slope in the linear fitting on S_{x10} (coefficient $p3$ in the plot 5a) means that the similarity between week 10 and the initial weeks is very low and increases with time. We can interpret it as a change in the movement patterns in the house between the beginning and the last weeks of the experimentation. In order to correlate this change to an actual increase in mobility, we plot also the local maxima number n over the weeks. In this way, we can infer that the user moves more in the apartment with time (n increases in a linear fitting with a positive slope coefficient $p1$).

On the contrary, in the control group flat (Figure 5b), the user does not change his movement patterns in the house (there is no relevant trend in the sequence of S_{x10}) and also the number of local maxima remains low ($p3$ and $p1$ respectively in Figure 5b).



(a) Intervention Group: $p_{x10} = 0.02$ with $p_m = 0.02$

(b) Control Group: $p_{x10} = -0.003$ with $p_m = 0.01$

Fig. 6: The surface plot of all the similarity indexes among the weeks of the DOREMI experimentation for an intervention group flat (a) and a control group flat (b). In the caption, the slope index relative to week 10 p_{x10} and the resulting median slope index p_m.

In order to have a more complete view of the user's indoor behavioral trend, we extracted the median slope index p_m over the entire DOREMI experimentation. Figure 6 shows a surface graph of all the similarity indexes among weeks for an intervention (a) and a control group flat (b) in UK, respectively. We can see that, for the intervention group flat the median value of all the similarity indexes for each week ($p_m = 0.02$ in Figure 6a) is higher than the value obtained from the control group flat ($p_m = 0.01$ in Figure 6b). The change in the indoor behavioral profile to a more dynamic life-style of the user living in the intervention group is also confirmed by the perseverance in performing the DOREMI exer-games and the general DOREMI protocol.

It is also worth noting that the graphs shown in Figure 6 give a quick overview of what happens inside the user both from a clinical and technical point of view. In particular, groups of cells with ones as values represent weeks identical in terms of sensors' activations among them. This can be interpreted as anomaly both from a technical aspect (e.g. the DOREMI gateway is malfunctioning) or from a user perspective (e.g. long periods away from home).

6 Conclusion

In this paper, we presented a novel approach for monitoring elderly behavior, by focusing on long-term monitoring of users' routine on the basis of indoor mobility. Instead of the cognitive approach, widely used in the field, we propose an emergent paradigm, based on stigmergy, that does not require a particular knowledge of the disease to be detected. An explicit modeling of the user's activities and behaviors 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 proposed system is able to detect behavioral deviations from the routine indoor activities on the basis of a generic indoor localization data inferred by means of environmental sensors' activations and a swarm intelligence method, namely stigmergy. The effectiveness of the proposed system has been tested on real-world AAL scenarios, in the framework of the DOREMI project.

In future work, we will evaluate how the proposed system can be applied on different sources of information, both raw (energy consumption, environmental sensors activations, and physiological measurements) and refined, as results of underlying subsystems not only related to indoor localization or activity recognition. The application of the stigmergic approach can be useful to detect emergent behavioral markers of diverse nature. We plan to refine the proposed algorithm to fit the sleep monitoring scenario, where the behavioral profile of the user is a key factor in order to detect anomalies related to sleep disorders [25, 26].

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