Detecting Elderly Behavior Shift via Smart Devices and Stigmergic Receptive Fields

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Abstract. Smart devices are increasingly used for health monitoring. We present a novel connectionist architecture to detect elderly *behavior shift* from data gathered by wearable or ambient sensing technology. Behavior shift is a pattern used in many applications: it may indicate initial signs of disease or deviations in performance. In the proposed architecture, the input samples are aggregated by functional structures called *trails*. The trailing process is inspired by *stigmergy*, an insects' coordination mechanism, and is managed by computational units called *Stigmergic Receptive Fields* (SRFs), which provide a (dis-)similarity measure between sample streams. This paper presents the architectural view, and summarizes the achievements related to three application case studies, i.e., indoor mobility behavior, sleep behavior, and physical activity behavior.

Keywords: Elderly monitoring · Smart sensing · Stigmergy · Neural receptive field · User's behavior shift

1 Introduction and Motivation

Today there is a great availability of smart devices for health, ranging from general purpose ones (such as phones, watches, clothes, shoes, and socks) for measuring steps, heart rate, body motion, etc., to special medical devices for measuring blood glucose, blood pressure, oximeter, and so on. The term *smart* is commonly due to: miniaturization, physical integration with everyday life, capability of autonomous connection and sharing data through the Web.

However, smart applications should also include mechanisms to prevent cognitive overload. As a matter of fact, most users when equipped with interfaces displaying data or simple activities, like heart rate or pedometer, lose interest after a short period of time. Studies have shown that monitoring and noticing *behavioral events* is more persuasive than displaying sequences of values or labels, because it requires less cognitive work and less user's conscious attention [1].

In the literature, many systems have been developed to detect daily activities, such as feeding, dressing, sleeping, walking, watching TV, etc. as a basis to represent human behavior [2]. The detection of daily activities usually deploys different techniques,

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including machine learning and probabilistic modeling, to deal with the inherent complex, user-dependent, time varying and incomplete nature of human-driven sensory data and behavioral logic. Actually, much work has to be done before such systems can be regularly managed. 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 explicit modeling and tracking of personal behavior. Moreover, when standardized daily activities are used by health professionals to assess the functional status of people, some important requirements exist: the monitoring system should use a limited amount of states, be highly flexible, handle uncertainty, and allow a personalization of what to monitor and how to notice it.

To cope with the above issues, we present a novel approach, consisting in two paradigm shifts: a different monitoring approach and a novel connectionist architecture with efficient setting and configuration.

The monitoring approach is based on a general-purpose wearable device and minimally affecting the subject's everyday life [3]. The widespread adoption of wearable devices offers an unprecedented opportunity of continuous monitoring of users' health [4]. For example, the use of commonly available smartphones to detect abnormal and potentially dangerous behavior – like falls or deviation in gait pattern – has been extensively investigated in the literature [5, 6]. However, exploiting smartphones to monitor health has some limitations: (i) smartphones are not carried by their users for long periods during the day (e.g., the smartphone may be placed on a desk while being at home); (ii) users can carry the smartphones at different body positions or even in a shoulder bag, making data analysis more difficult and less trustworthy. In this context, a great enhancement could be represented by the adoption of wrist-worn devices, like smartwatches or smart bracelets. These devices can be worn continuously to enable deep analysis of mobility and sleep patterns. Moreover, the position and orientation of the device with respect to the user's body is known in advance. We remark that the approach focuses on detecting *user's behavior shift*, a pattern used here to indicate initial signs of disease [7]. Detection of explicit user activities and diagnosis of specific diseases are not within the scope of the approach.

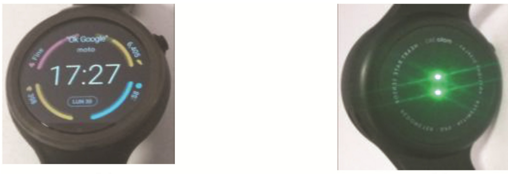
The proposed architecture relies on advanced bio-inspired techniques to simplify the management effort. In the proposed architecture, the input samples are aggregated by functional structures called *trails*. The trailing process is inspired by *stigmergy* [2, 8], an insects' coordination mechanism, and is managed by computational units called *Stigmergic Receptive Fields* (SRFs), which provide a (dis-) similarity measure between sample streams. SRFs are organized into a multilayer system, and adapted to contextual behavior by means of the Differential Evolution (DE) algorithm [9]. Thus, the novelty of the undertaken study relates to the structure of a receptive field and the way in which such receptive fields are formed and adapted.

The concept of receptive field derives from a computational mechanism employed by biological information processing systems [10]. In our approach to digital information processing, it relates to an architectural style consisting of a collection of general purpose local models (archetypes) that detects a micro-behavior of the entire modeling domain. Since micro-behavior is not individual, a receptive field can be reused for a broad class of patients/users: the use of SRF is then proposed as a more general and effective way of designing micro-pattern detection. Moreover, SRF can be used in a multilayered architecture, thus providing further levels of processing so as to realize a macro analysis.

The paper is structured as follows. Section 2 focuses on the system architecture, including the smart devices adopted, the structure and topology of a multilayer architecture. In Sect. 3, three application case studies are presented. Finally, Sect. 4 summarizes conclusions and future work.

2 System Architecture

In our research different smartwatches and localization systems have been used, differing on accuracy, type of input data, battery duration, and so on. The research regarding sleep analysis was carried out using an *LG Watch R* smartwatch, which ensures battery duration higher than 8 h. The study on physical activity was based on a *Moto 360 Sport* smartwatch (Fig. 1), which provides better accuracy. Both models include an accelerometer, gyroscope, barometric altimeter, and optical hearth rate monitor (PPG), and can be combined with ambient sensors to achieve accurate indoor positioning of the user. An indoor positioning system used in the study of the mobility behavior is the *n-Core* localization system, which exploits a mobile unit worn by the user and a static ZigBee wireless network [2]. This system combines measures such as Receive Signal Strength and Link Quality Indicator with a set of locating techniques to track users' position in real time.



(a) (b)

Fig. 1. (a) Front side and (b) back side of the Moto 360 Sport smartwatch.

The processing system periodically takes samples of the user activity parameters as an input and releases a *mark* in a computer-simulated spatial environment, thus allowing the accumulation of marks as a *trail*. A mark is a trapezoid with three attributes: intensity (height), width, and position. The position corresponds to the value of the sample where the mark is left. Mark intensity proportionally decreases with the distance from the position. Mark intensity in the trail has a temporal decay (the percentage of intensity decreased after a step of time). Hence, an isolated mark after a certain time tends to disappear. The time that a mark takes to disappear is longer than the period taken by the system to release a new mark; thus, consecutive samples close to a specific value (clump) will superimpose, so increasing the trail intensity. The trail can then be considered as a short-term and a short-size action memory. Thanks to the width, the trail captures a coarse spatiotemporal structure in the domain space, which hides the micro-complexity and the micro-variability in data. Trails of different sample streams can be compared to provide a degree of similarity between a current micro-behavior, represented by a segment of the time series, and a reference (or archetype) micro-behavior, referring to a pure form time series which embodies a behavioral class. An example of class is *raising heartbeat*, which means that the heartbeat shows a sudden increase of level over time.

The similarity processing is managed by the SRF. Furthermore, an SRF is adaptive: its structural parameters, such as the mark attributes, are tuned by means of the DE algorithm. The use of SRFs is proposed as a more general and effective way of designing micro-pattern detection. Moreover, SRF can be used in a multilayered architecture, thus providing further levels of processing so as to realize a macro analysis. Figure 2 shows the structure of a single SRF. Here, the input is made of the data sample of the reference signal $\bar{d}(k)$, represented in gray color, together with the data samples of the current signal $d(k)$, which periodically feed the SRF. The first three processing modules of the SRF are exactly the same for the reference and the input segment. The modules of the reference signal are represented as gray shadow of the corresponding modules of the input segment.

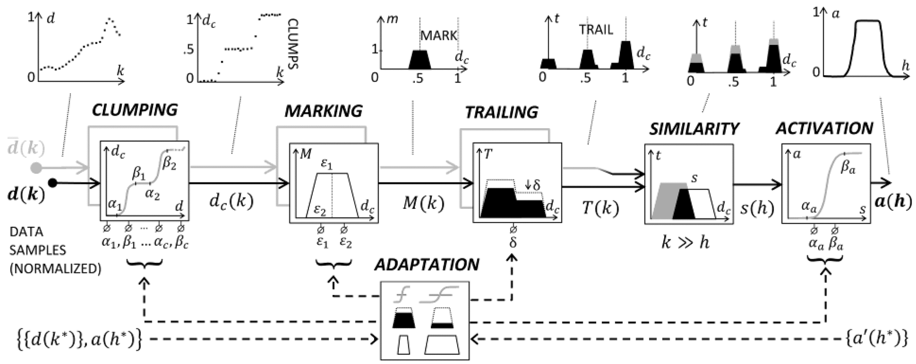


Fig. 2. Structure of a stigmergic receptive field.

A normalization of the continuous-valued samples is assumed. First, normalized data samples undergo the *clumping process*, which is a kind of soft discretization of the samples to a set of levels. Second, the *marking* process produces a *mark* corresponding to each data sample and represented as a trapezoidal form in figure. Third, the *trailing* process creates the *trail* structure exploiting the accumulation and the evaporation over time of the marks. Fourth, *similarity* compares the current and reference (or archetype) trails. Fifth, *activation* increases/decreases the rate of similarity. Here, the term "activation" is taken from neural sciences and it is related to the requirement that a signal must reach a certain level before a processing layer can fire to the next layer [11].

Each SRF should be properly parameterized to enable an effective samples aggregation and output activation. For example, short-life marks evaporate too fast, preventing aggregation and pattern reinforcement, whereas long-life marks cause early activation. The *adaptation* module uses the DE algorithm to adapt the parameters of the SRF with respect to the fitness, which is computed over a tuning set. In Fig. 2 the tuning set is denoted by asterisks: it is a sequence of *(input, desired output)* pairs, represented on the left. In a fitting solution, the desired and *actual output* values (represented on the right) are very close.

Figure 3(a) shows the topology of a *stigmergic perceptron*. In neurocomputing, a perceptron computes a single output value from multiple input values, by forming a linear combination of them, parameterized for achieving some desired mapping. Similarly, the stigmergic perceptron detects the similarity between many reference signals (or archetypes) and the current input samples by forming a linear combination of the most similar SRFs, parameterized for achieving some desired mapping [10].

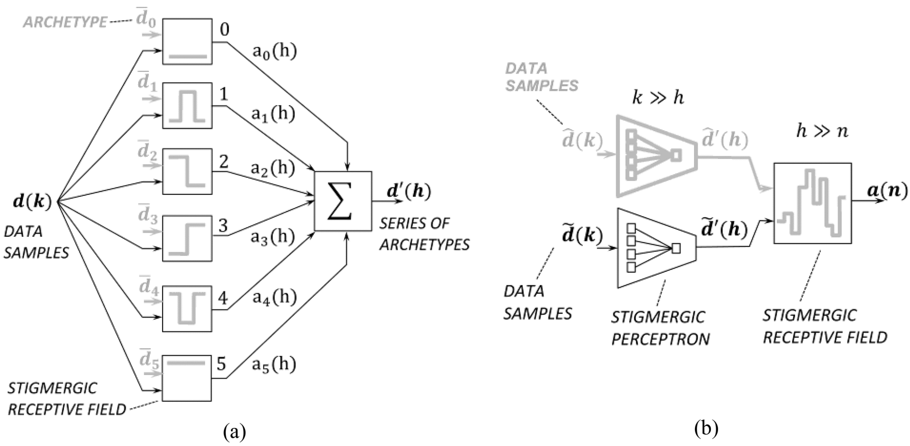


Fig. 3. (a) Topology of a stigmergic perceptron. (b) Topology of a multilayer architecture of SRF.

More specifically, Fig. 3(a) shows six SRFs, whose archetypes are mapped to the natural-valued interval [0, 5]. In the output layer, the average of such natural numbers weighted by the SRF activations is calculated, to provide a linear combination of neighboring archetypes in the real-valued interval [0,5]. Figure 3(b) shows the topology of a multilayer architecture of SRFs. In the first layer, each SRF is fed with the input data series, to provide the degree of similarity to each archetypal pattern. The activation of each SRF is then used to generate a higher level time series through the stigmergic perceptron. In the next layer, another SRF is used to provide the degree of similarity between two time series of archetypes, i.e., current and reference time series. Here, the adaptation is based on similarity samples provided by a human expert. This layer carries out a macro-level similarity between two time series.

An interesting property of the proposed approach is that 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. Indeed, stigmergy preserves privacy since it controls the level of perturbation of information, which means that information is scrambled to be partially hidden but up to preserve its utility. Stigmergy allows masking plain information by replacing it with a mark, as a surrogate keeping some piece of the original information. Furthermore, analog data provided by marker-based stigmergy allows measurements with continuously changing qualities, suitable for multi-valued classification.

3 Application Case Studies

This Section summarizes three application case studies: indoor mobility behavior, sleep behavior, and physical activity behavior.

The research on *indoor mobility behavior* aims to monitor elderly people living alone in their houses, by using a localization system [2]. The purpose is to face in a more proactive and preventive way age-related chronic diseases such as depression, cardiac insufficiency, arthritis, and so on. Indeed, disease situations initially lack noticeable symptoms and then do not cause emotional involvement that could activate decision-making, but gradual deviations of generic behavioral patterns such as mobility or vital parameters. The indoor position of the elderly is periodically estimated by a localization system, and taken as an input to the monitoring system. The similarity between the current and a reference track senses 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 long-term period of stable health conditions by a relative and a healthcare professional. The system has analyzed the data collected by a woman aged 90, affected by depression, who has been monitored for 24 days. The system was able to detect behavioral shift caused by depression symptoms, such as decreased appetite and withdrawal from socializing, increased total sleep time and nocturnal awakenings.

The research on *sleep behavior* aims to detect sleep deprivation [12, 13]. Chronic sleep deficit has been linked to long-term health issues such as diabetes, high blood pressure and heart disease, and recent studies suggest that it is the real cause of burnout. Recently developed smart-watches have been used for monitoring sleep patterns variation, because they can also feature sensors. Sensed data, i.e. heartbeat rate and wrist acceleration, are processed to produce a sleep stigmergic trail of the watch wearer. By comparing the current stigmergic trail to a trail produced in normal sleeping, it can be derived a sort of digital sleep diary, enabling the doctor to accurately diagnose any disorder. The system has analyzed the data collected by a woman aged 88, affected by arterial hypertension, who has worn a smartwatch during 20 nights. As a result, the system was able to detect behavioral shift caused by awakenings and an overall sleep quality.

The research on *physical activity behavior* is a part of a larger project whose purpose is to detect frailty in older adults [14]. Physical activity is important for healthy ageing. Better insight into objectively measured activity levels in older adults is needed, since most previous studies employed self-report. This is particularly important for the elderly population, as a healthier lifestyle would enable independent living to occur for a longer period of time. The effect of leading an increasing sedentary lifestyle is also not evident straightaway. Thus, an alert on a behavioral shift event is significant to the user. Data have been collected among 60 + , 70 + and 80 + years old subjects, measuring heartbeat rate, acceleration and pedometer in a variety of physical activity levels. The system generates an activity trail of the elderly, which can be compared with a reference trail to provide physical activity levels. As a result, it is able to detect behavioral shift caused by physical weakness and loss of strength.

The first experimentation of the proposed system was carried out in the indoor mobility behavior study. Subsequently, the system was improved with additional modules/features, and then experimented in the sleep behavior study. Recently, modules/features have been included for the study on physical activity behavior. The modules/features experimented in each application case study are shown in Table 1.

Table 1. Case studies and related modules/features experimented.

Module/Feature type	Application case study and related module/feature		
	Indoor mobility behavior	Sleep behavior	Physical activity behavior
Smart device	Localization system	Smartwatch	Smartwatch
Sampling rate	1 sample/5 min.	10 samples/s	10 samples/s
Input	- Indoor position	- Wrist acceleration - Heartbeat rate	- Wrist acceleration - Heartbeat rate - Pedometer
1D/2D Input	2D	1D	1D
Processing modules	- Marking - Trailing - Similarity - Activation	- Normalization - Clumping - Marking - Trailing - Similarity - Activation - Adaptation - Perceptron - Multilayer	- Normalization - Clumping - Marking - Trailing - Similarity - Activation - Adaptation - Perceptron - Multilayer - Multichannel
Output	Behavioral shift caused by depression	Behavioral shift caused by awakenings and sleep quality	Behavioral shift caused by physical weakness and loss of strength
Subject	Woman aged 90	Woman aged 88 Man aged 72	Men aged 60+, 70+, 80+
Observation period	24 days	20 nights	30 days

4 Conclusions and Future Work

This paper summarizes our research activity on monitoring *elderly behavior shift*. A novel approach based on stigmergic computing paradigm and smart devices is proposed. The challenges in the field are outlined, the novel architectural approach is illustrated and applied to three different application case studies. The proposed architecture has been developed and experimented, making possible the initial roll-out of the approach into real environments. Other pilot case studies are currently undertaken, to demonstrate that the system is effective in achieving the expected performance on a number of cases.

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