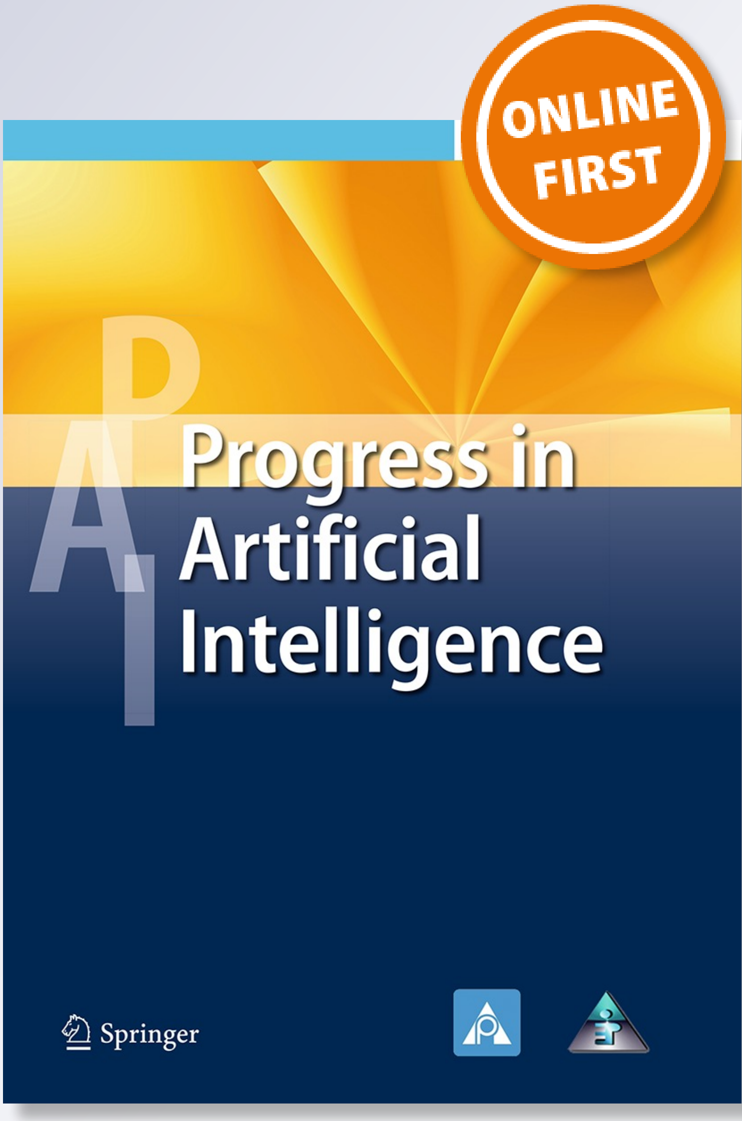
The role of non-intrusive approaches in the development of people-aware systems

Paulo Novais & Davide Carneiro

Progress in Artificial Intelligence

ISSN 2192-6352

Prog Artif Intell
DOI 10.1007/s13748-016-0085-1



Prog Artif Intell
DOI 10.1007/s13748-016-0085-1

REGULAR PAPER

The role of non-intrusive approaches in the development of people-aware systems

Paulo Novais[1] · **Davide Carneiro**[1]

Received: 5 January 2016 / Accepted: 31 January 2016

Abstract There is currently a significant interest in consumer electronics in applications and devices that monitor and improve the user's well-being. This is one of the key aspects in the development of ambient intelligence systems. Nonetheless, existing approaches are generally based on physiological sensors, which are intrusive and cannot be realistically used, especially in ambient intelligence in which the transparency, pervasiveness and sensitivity are paramount. We put forward a new approach to the problem in which user behavioral cues are used as an input to assess inner state. This innovative approach has been validated by research in the last years and has characteristics that may enable the development of true unobtrusive, pervasive and sensitive ambient intelligent systems.

Keywords Ambient intelligence · Behavioral analysis · Human–computer interaction · Stress

1 Introduction

A lot has been said and written about the possibilities of ambient intelligence [7,8,15] since the introduction of the term, back in 1998. At the time, it was viewed as a significant change in consumer electronics, in which interesting features were scattered and fragmented in independent devices, towards a new reality in which these features would be readily available, in the form of services, regardless of device or location.

The hype was such that, 2 years after the introduction of the term, the Information Society Technologies Advisory Group (ISTAG) put forward several scenarios that would be reality 10 years after, in 2010 [17]. Knowing the current state of research and of consumer electronics, it is clear that the future envisioned in these scenarios is far from being reality. At least, it is far from being reality for 'ordinary people', as envisioned.

Four specific scenarios were described, of which the second is closest to the topic of this paper. It describes 'D-Me' (Digital-Me) as an avatar of the user, which constantly monitors the user's behaviors, so as to build a complete and up-to-date profile. This avatar, embodied in the clothes of the user, can then take some decisions that resemble the ones that would be (and were) taken by the user, in similar situations.

There is no need to dwell on the fact that nowadays, 5 years past the envisioned 2010, most of these scenarios are nearly as fictional as they were in 2001, despite some advances. The reasons for this are numerous and, interestingly, often increase with each technological advance, i.e., the steps taken to implement these scenarios often raise challenges of their own.

Cook et al. [14] summarize the main characteristics of AmI systems: sensitive, responsive, adaptive, transparent, ubiquitous, and intelligent. Some of these characteristics depend on technological evolution. For instance, *ubiquitous* and *transparent* depend on advances in pervasive computing. *Intelligent* depends, mostly, on contributions of certain fields of Artificial Intelligence. If the question is now on what the *sensitive* characteristic depends, the logical answer is that it depends on advances in sensors and sensor networks.

✉ Paulo Novais
pjon@di.uminho.pt

Davide Carneiro
dcarneiro@di.uminho.pt

1 Algoritmi Center/Department of Informatics, Universidade do Minho, Braga, Portugal

To some extent, this answer is correct. However, if that is the whole answer, we are clearly reducing the problem. In fact, evolution in this aspect is not only dependent on smaller, cheaper or more reliable or connected sensors. Moreover, one should not only consider the so-called hard sensors (traditional sensors, in the physical sense, made of specifically designed hardware). Evolution may also come from the so-called soft sensors: virtual (software-based) sensors, especially useful in data fusion, where measurements of different characteristics and dynamics are combined.

In fact, in a human-centered perspective, *sensitive* may involve aspects as complex and diverse as our level of stress, our level of fatigue, our state of arousal or our emotional state, just to name a few. All this information is very important for a proper AmI system, especially one that is sensitive, responsive and adaptive. And, there are nowadays approaches to acquire this information. These approaches, which we deem as "traditional" are based on physiological sensors (e.g., electro-dermal activity, heart rate, respiratory rate, electroencephalography) and are very accurate. They are, however, and most of the times, impracticable.

In this paper, we argue that approaches based on physiological sensors are one of the reasons holding back a truly sensitive and adaptive AmI. Especially because they cannot be realistically used to acquire the necessary information: no users will walk around continuously connected to a number of sensors so as to have an application that can monitor their state during the day. We also argue that the answer to this problem is a new approach based on behavioral analysis. It is non-intrusive, fully integrates the main characteristics of AmI and may constitute an important step for the development of AmI systems. Other authors have also investigated this approach, namely for emotion classification and intrusion detection [18,19,35].

The remaining of the paper is organized as follows. Section 2 describes traditional approaches to the problem of data acquisition from people, arguing that such methods are not compatible with the AmI vision. Section 3 details the proposed new view on the problem in a critical and uncompromised way: it clearly addresses the criticism to this approach, the opportunity it represents, its technological feasibility and market acceptance. Finally, Sect. 4 summarizes the main aspects addressed in the paper.

2 Traditional approaches

Traditionally, two main approaches can be followed to quantify the effects of stress: (1) questionnaires or surveys, used mostly by psychology and (2) physiological sensors. Each of these has particular advantages and disadvantages when considered to be used in the implementation of AmI systems.

Questionnaires, as other self-reporting mechanisms, are seen as an inexpensive approach to collect vast amounts of information. They do not represent a very significant effort for the researcher, who also benefits from the easiness in compiling data, which results from a set of predefined answers [1]. These instruments are eminently practical and can be administered either by the researcher or by anyone else, possible remotely, without affecting validity or reliability. Given that they are clearly impractical to be used in real settings of AmI, asides from other disadvantages [30], they will not be addressed further in this paper.

Alternatively, technological advances and medical research led to a highly precise approach to the problem, based on a range of sensors that measure physiological or neurological effects of processes such as stress, fatigue or emotions on the human body. Skin conductivity, for instance, measures the skin resistance to electric current, which varies according to the level of perspiration. Given that sudoriparous glands are controlled by the sympathetic nervous system, they unveil mental states associated to psychological or physiological arousal, which take place during peaks of stress. Skin temperature, heart rate or respiratory rate are also well-known indicators for the study of stress, emotions or fatigue [3,23]. Hearth rate variability, defined as the variation of the time between heartbeats, has also been increasingly used to study stress [6], showing that both are closely connected.

The steep growing of biofeedback tools is also noteworthy. These tools combine feedback from multiple bodily functions, using instruments that analyze indicators such as brain waves, muscular response, skin conductivity, heart rate or pain perception [34]. The study of brain waves is particularly interesting since it provides clues about our inner state in a very thorough way, allowing to compare, at the simultaneous comparison of related phenomena. These tools can also be used to improve certain aspects such as daily habits or behaviors, since they provide real-time feedback to the user [25].

Approaches based on physiological sensors are very precise and are used not only to evaluate the state of an individual but also as a basis for medical treatments. Their use and validity are nowadays unquestionable. However, in the context of this work, both approaches (physiological sensors and questionnaires) are analyzed considering their use in a real AmI setting. In that sense, it becomes necessary to ascertain the extent to which these approaches are suitable to be used in these milieus. Our claim is that they cannot be realistically used without negative side effects.

3 A new view on the problem

In the last years, an alternative approach has been emerging that may constitute not only a change in the paradigm of data acquisition but also support the development of *real*

AmI systems, in the sense that they can simultaneously be *sensitive* and *transparent*. That is, AmI systems in which the user is constantly being monitored but in a way that is completely non-intrusive and transparent. Ultimately, the user forgets about the monitoring and notices only the environment's contextualized actions.

This new view on the problem is based on behavioral analysis [37]. Here, everything the user does (e.g., interactions with devices, movement patterns, interactions with other users) can be used as a potential input. Moreover, one can consider not only what the user does but *how* the user does it.

In fact, our behaviors are commonly associated with our inner states. We look at someone who is restless, biting the nails or fiddling and we instantly know that the person is nervous or stressed. We look at someone who is moving slow, whose eyes are half closed and who gets distracted easily and we now that the person is tired. The fact is that, in an interaction, our behaviors often give away more information than the words we use. And we, as humans, have evolved to collect this information to, even in an unconscious way, better understand the state of the other individual. This information is actually paramount for the efficiency of the communication process [16].

The challenge thus lies in developing ways to acquire this information and use it as a way to perceive the user's inner state. As will be detailed in Sect. 4, many of our behaviors can be used as input to classify our state. Namely, the way we type in a keyboard, the way we move the mouse, the way we hold or touch our smartphone, the way we talk or even the way we sit. While one of these features may not be enough to accurately describe the user's state, their combined used may constitute a reliable source of information.

The main advantage of this approach is, undoubtedly, that it can be used continuously throughout the day, without interfering with the users' routines. It is transparent, non-intrusive and pervasive. It allows for behavioral models to be trained in short time frames that allow to know one's frequent behaviors when in neutral states as well as in specific states. These models can be dependent on many variables (that can also be acquired by the environment) including geographical, social or historic context. There is, however, criticism to this approach, which is analyzed in the following section.

3.1 Criticism

The first natural criticism to this new behavioral approach is that it is not as precise as physiological sensors. Indeed, that is a fact that must be acknowledged. However, it is also important to keep in mind that we advocate this approach in contexts in which sensors cannot be realistically used by the user without interfering with the routines. That is, we search truly transparent approaches, in line with the fundamental characteristics of AmI. In this context, behavioral approaches may well be the most suited ones.

Moreover, and in what concerns the reliability of these approaches, our own previous work shows that it is possible to use our touch patterns in a smartphone, our interaction patterns with the computer or our movements in the chair to classify processes such as mental fatigue or stress, in environments such as workplaces or classrooms [10,28,29]. In fact, some indicators are so reliable that they can be used even for authentication purposes, in what is known as Behavioral Biometrics—the use of behavioral traits of the individual for identification and access control. An example application is a computer that asks for a password if it detects that the user is typing in a significantly different way than usual, which may mean that there is a non-authorized user accessing the computer [2].

We thus believe that a sufficient reliability of these approaches can be guaranteed. Another perhaps more challenging issue, often disregarded by computer scientists, concerns privacy, identity and security issues. Friedewald et al. [20] make a thorough analysis of 70 AmI projects concerning these issues. They conclude that in general, current projects present a rather too sunny view of our technological future, ignoring or postponing dealing with some pressing issues. The authors also make an interesting reference to he SWAMI project (Safeguards in a World of Ambient Intelligence) which, against this trend, has constructed what they deemed "dark" scenarios [38], to show how things can go wrong in AmI and where safeguards are needed. Once again, some of these safeguards had already been put forward by [17], while others emerged more recently. As Rouvroy and Brey separately put it, the challenge here is to preserve the individual freedom to build one's own personality without excessive constrains and influences while have control over the aspects of one's identity that one projects on the world [5,32].

Marzano, on a different view, looks at the cultural implications of an unregulated or indiscriminate growth of AmI, making a parallel with the industrial revolution [26]. As later was proved to be, more was not necessarily better at the time: take for instance consequences such as the pollution. Right now, *smarter* may also not be necessarily better. Indeed, we may simply not want a smart juicer or a talking toaster. The decisions we make now will shape us as a society in the future, as the decisions in the industrial revolution resulted in today's society, for the better and the worse.

While an argument can be (and has been) made against the first criticism, the other aspects mentioned are far more complex. They involve more abstract notions such as ethics, and are difficult to address, study and validate in laboratory settings. Indeed, multidisciplinary efforts must be encouraged in order to address these questions with the possible detail. However, at the end, it will always be the public that will decide whether or not this trade-off between providing access to inner states and gaining truly AmI systems is worth it. As detailed in Sect. 4, we believe it is.

3.2 The opportunity

There is a huge opportunity laying in the development of methods for the acquisition of behavioral data. First of all, there is the possibility of learning how we behave as individuals and as a society in certain situations and in certain states. From a crowd-sourcing point of view, it could be used to measure the state of the society at different levels or granularity. For example, it could be used to monitor in which parts of a city people are more stressed (e.g., a specific neighborhood) in order to improve it. It could also be used to track changes in people's states over long periods of time. Similar initiatives could be implemented at a personal level (e.g., personal monitoring applications) or at an organizational level (e.g., tracking the fatigue of employees).

One good example of non-intrusively tracking information about thousands of users is CrowdSignals.io.[1] CrowdSignals.io will create the largest set of rich, longitudinal mobile and sensor data recorded from smartphones and smartwatches. The dataset will include geo-location, sensor, system and network logs, user interactions, social connections, and communications as well as user-provided ground truth labels and survey feedback. The main goal of the project is to enable researchers worldwide across a variety of fields to collect the data they need to solve important societal problems.

Another similar approach combines social media, crowdsourcing and Artificial intelligence with the aim of identifying and relieving disaster areas. Tweets, tagged images, hashtags, and disaster victims reporting their experiences on social media can all be added to a map of the disaster area in order to determine where the area was most heavily hit, allowing for a better management of resources. Once again, users do not explicitly provide this information to a special-purpose application. Instead, the information is mined from existing platforms that the users would use anyways.

This knowledge, by itself, can be very important to understand ourselves and each other. However, true opportunities lay in what we can do with this information. In a few words, the opportunity in these new approaches is, in our opinion, the opportunity to implement true AmI systems, in the sense that there are no visible sensors, no wires, no hardware, no intrusion. True also in the sense that they cab be always on, always monitoring, always acting accordingly.

[1] The web site of CrowdSignals.io is available at http://crowdsignals.io/ <accessed in December, 2015>.

4 Feasibility and acceptance

With regard to the feasibility of this new approach, and based on a number of existing projects, we are convinced that it is technologically feasible. Let us analyze some specific examples. In [27] the authors address the problem of people not wanting to touch biometric scanners through the use of palm movements as effective behavioral biometric modality. In our own previous work, we have shown how the way we touch the screen of a smartphone consistently changes with stress [10,11], as well as our interaction with the computer, namely in e-learning environments [31]. We have also proved that our level of mental fatigue alters, in a consistent way, our interaction patterns with the keyboard and mouse of the computer [28]. Finally, we have also shown that even more abstract notions, such as personal conflict handling styles, can be predicted from the observation of the behavior [9].

Other researchers have also looked at the problem of classifying the level of stress, taking as input the voice of the users. Xie et al. [39] use speaker-independent prosodic features and vowel quality features as terminals to classify each vowel segment as stressed or unstressed. A similar approach is followed by Zhao et al. [40]. Castillo et al. [12] use a non-intrusive approach to classify user activities and, most importantly, detect falls. In a related approach, Stucki et al. [36] use wireless sensors distributed in every room of the participant's home to develop a non-intrusive system, which does not use body-mounted sensors, video-based imaging, and microphone recordings to monitor activities. Finally, González et al. [22] present a noise-robust algorithm for segmentation of breath events during continuous speech . The built-in microphone of a smartphone is used to capture the speech signal (voiced and breath frames) under conditions of a relatively noisy background.

Many more examples of non-intrusive methods for acquiring relevant information about the users could be mentioned. The examples provided are, however, enough to support our claim: it is nowadays possible to develop non-intrusive methods for acquiring very different types of information about the users. The important question that remains is: do users want to use them?

The aspect that will define the evolution of AmI systems towards this kind of methods is whether users will adhere to them or not. That is, do users of consumer electronics want an application or system that continuously monitor their interaction patterns, their localization, their social connections or the way they interact with the devices? We believe that it all comes down to the other side of the trade-off, that is, what do they get in return? It is our conviction that if these systems provide, as return, high-value services for the users, then users will allow the collection of this type of information, provided that there is full transparency regarding the collected data and the information compiled.

Indeed, there are already many applications and devices in the market that collect data and compile high-level information about the state of the user, in exchange for services of high-value. Some of these applications or systems may still be based on intrusive techniques, which means that an evolution towards behavioral-based approaches may increase their use even more, given that they will be more comfortable to use.

Kailas et al. [24] provide a very good overview of this still new trend and how users may benefit from it, especially in terms of health-care and well-being. A quick search on the most popular application markets also reveals that there are developers dedicated to this, as well as interested users. Taking as example Android's Google play, general-purpose and free applications can be easily found with names such as "Stress Check", "Stress Viewer" or "Stress Releaser". Other more specific applications that require special hardware can also be found, such as "PIP Stress Tracker", which uses an electro-dermal activity sensor to track stress.

Another important group of applications also exists that is centered on techniques to cope with stress or fatigue, such as regular breathing exercises or social activities. An example of such is Android's "Destressify".

Several research projects can also be pointed out in this domain. Sanches et al. [33] look at changes in the speech production process as one of many physiological changes that happen during stress. They thus use microphones, embedded in mobile phones and carried ubiquitously by people, to continuously and non-invasively monitor stress in real-life situations. Colunas et al. [13] use Android smartphones to monitor, in real-time, the elements of a team. This approach, however, requires the use of Vital Jacket (a jacked with embedded sensors). On a purely behavioral approach, Bauer and Lukowicz [4] describe how changes in the behavior of the users of a smartphone can be detected to classify stress. Finally, Gaggioli et al. [21] present a system that mixes physiological sensors and behavioral analysis, in an hybrid and accurate approach.

Firstly, it is clear that there is an interest from the research community in behavior-based approaches. Secondly, users of consumer electronics also have interest in this kind of applications and, as far as it is possible to tell by the increasing number of applications on the subject, consumers do not see a problem in behavioral analysis for the purpose of increasing well-being.

5 Conclusions

In this paper, we addressed the relatively low pace at which ambient intelligence is evolving. We argued that one of the reasons for this lies in the lack of suitable approaches for acquiring contextual information regarding users, without which no simultaneously sensitive, pervasive and transparent AmI systems will ever be achieved.

We addressed how current approaches, based mostly on physiological sensors, cannot realistically be used to collect this kind of data, especially because they are highly intrusive, require specific hardware to be used and may cause changes in the users' routines. Finally, we put forward an alternative approach that is based on behavioral cues of the users. Instead of using physiological signs, this new view on the problem considers behavioral cues that have a relationship with our inner state.

As described, this new approach considers new types of information that can be acquired and compiled in a true non-intrusive way. We also address some of the potential problems, namely with regard to privacy. Nonetheless we conclude that, as current trends show, users are willing to pay the price in order to get applications and hardware that may result in a significant improvement of their well-being.

Acknowledgments This work has been supported by FCT -Fundação para a Ciência e Tecnologia within the Project Scope UID/CEC/00319/2013. The work of Davide Carneiro is supported by a Doctoral Grant by FCT (SFRH/BPD/ 109070/2015).

References

1. Ackroyd, S.: Data Collection in Context. Longman Group, UK (1992)
2. Ahmed, A.A.E., Traore, I.: Detecting computer intrusions using behavioral biometrics. In: PST, Citeseer (2005)
3. Barreto, A., Zhai, J., Adjouadi, M.: Non-intrusive physiological monitoring for automated stress detection in human–computer interaction. In: Lew M, Sebe N, Huang TS, Bakker EM (eds) Human–Computer Interaction, pp. 29–38. Springer, Berlin (2007)
4. Bauer, G., Lukowicz, P.: Can smartphones detect stress-related changes in the behaviour of individuals? In: 2012 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), IEEE, pp. 423–426 (2012)
5. Brey, P.: Freedom and privacy in ambient intelligence. Ethics Inform. Technol. **7**(3), 157–166 (2005)
6. Brüser, C., Stadlthanner, K., De Waele, S., Leonhardt, S.: Adaptive beat-to-beat heart rate estimation in ballistocardiograms. IEEE Trans. Inform. Technol. Biomed. **15**(5), 778–786 (2011)
7. Carneiro, D., Novais, P.: New applications of ambient intelligence. In: Ramos C, Novais P, Nihan CE, Corchado Rodríguez JM (eds) Ambient Intelligence-Software and Applications, pp. 225–232. Springer, Berlin (2014)
8. Carneiro, D., Costa, R., Novais, P., Neves, J., Machado, J., Neves, J.: Simulating and monitoring ambient assisted living. In: Proceedings of the ESM, pp. 175–182 (2008)
9. Carneiro, D., Gomes, M., Novais, P., Neves, J.: Developing dynamic conflict resolution models based on the interpretation of personal conflict styles. In: Antunes L, Pinto HS (eds) Progress in Artificial Intelligence, pp. 44–58. Springer, Berlin (2011)
10. Carneiro, D., Castillo, J.C., Novais, P., Fernández-Caballero, A., Neves, J.: Multimodal behavioral analysis for non-invasive stress detection. Expert Syst. Appl. **39**(18), 13,376–13,389 (2012a)
11. Carneiro, D., Montotya, J.C.C., Novais, P., Fernández-Caballero, A., Neves, J., Bonal, M.T.L.: Stress monitoring in conflict reso-

lution situations. In: Novais P, Hallenborg K, Tapia DI, Corchado Rodríguez JM (eds) Ambient Intelligence-Software and Applications, pp. 137–144. Springer, Berlin (2012b)
12. Castillo, J.C., Carneiro, D., Serrano-Cuerda, J., Novais, P., Fernández-Caballero, A., Neves, J.: A multi-modal approach for activity classification and fall detection. Int. J. Syst. Sci. **45**(4), 810–824 (2014)
13. Colunas, M.F., Fernandes, J.M.A., Oliveira, I.C., Cunha, J.P.S.: Droid jacket: using an android based smartphone for team monitoring. In: 2011 7th International Wireless Communications and Mobile Computing Conference (IWCMC), IEEE, pp. 2157–2161 (2011)
14. Cook, D.J., Augusto, J.C., Jakkula, V.R.: Ambient intelligence: technologies, applications, and opportunities. Pervas. Mobile Comput. **5**(4), 277–298 (2009)
15. Costa, R., Novais, P., Machado, J., Alberto, C., Neves, J.: Interorganization cooperation for care of the elderly. In: Wang W, Li Y, Duan Z, Yan L, Li H, Yang X (eds) Integration and Innovation Orient to E-Society, vol. 2, pp. 200–208. Springer, Berlin (2007)
16. Dennis, A.R., Kinney, S.T.: Testing media richness theory in the new media: the effects of cues, feedback, and task equivocality. Inform. Syst. Res. **9**(3), 256–274 (1998)
17. Ducatel, K., Bogdanowicz, M., Scapolo, F., Leijten, J., Burgelman, J.C.: Scenarios for ambient intelligence in 2010. Office for official publications of the European Communities (2001)
18. Epp, C., Lippold, M., Mandryk, R.L.: Identifying emotional states using keystroke dynamics. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, pp. 715–724 (2011)
19. Ferreira, J., Santos, H.: Keystroke dynamics for continuous access control enforcement. In: 2012 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC), IEEE, pp. 216–223 (2012)
20. Friedewald, M., Vildjiounaite, E., Punie, Y., Wright, D.: The brave new world of ambient intelligence: an analysis of scenarios regarding privacy, identity and security issues. In: Clark JA, Paige RF, Polack FAC, Brooke PJ (eds) Security in Pervasive Computing, pp. 119–133. Springer, Berlin (2006)
21. Gaggioli, A., Pioggia, G., Tartarisco, G., Baldus, G., Ferro, M., Cipresso, P., Serino, S., Popleteev, A., Gabrielli, S., Maimone, R., et al.: A system for automatic detection of momentary stress in naturalistic settings. Stud. Health Technol. Inform. **181**, 182–186 (2012)
22. González, I., Carretón, C., Ochoa, S.F., Bravo, J.: Towards a non-intrusive self-management system for asthma control using smartphones. In: Hervás R, Lee S, Nugent C, Bravo J (eds) Ubiquitous Computing and Ambient Intelligence. Personalisation and User Adapted Services, pp. 44–47. Springer, Berlin (2014)
23. Healey, J., Picard, R.W., et al.: Detecting stress during real-world driving tasks using physiological sensors. IEEE Trans. Intell. Transp. Syst. **6**(2), 156–166 (2005)
24. Kailas, A., Chong, C.C., Watanabe, F.: From mobile phones to personal wellness dashboards. Pulse IEEE **1**(1), 57–63 (2010)
25. Lubar, J.F.: Discourse on the development of eeg diagnostics and biofeedback for attention-deficit/hyperactivity disorders. Biofeedback Self-regul. **16**(3), 201–225 (1991)
26. Marzano, S.: The New Everyday: Views on Ambient Intelligence. 010 Publishers (2003)
27. Piekarczyk, M., Ogiela, M.R.: On using palm and finger movements as a gesture-based biometrics. In: 2015 International Conference on Intelligent Networking and Collaborative Systems (INCOS), IEEE, pp. 211–216 (2015)
28. Pimenta, A., Carneiro, D., Novais, P., Neves, J.: Monitoring mental fatigue through the analysis of keyboard and mouse interaction patterns. In: Pan J-S, Polycarpou MM, Wozniak M, de Carvalho ACPLF, Quintián H, Corchado E (eds) Hybrid Artificial Intelligent Systems, pp. 222–231. Springer, Berlin (2013)
29. Pimenta, A., Carneiro, D., Novais, P., Neves, J.: A discomfort-sensitive chair for pointing out mental fatigue. In: Mohamed A, Novais P, Pereira A, González GV, Fernández-Caballero A (eds) Ambient Intelligence-Software and Applications, pp. 57–64. Springer, Berlin (2015)
30. Popper, K.: The Logic of Scientific Discovery. Routledge, London (2005)
31. Rodrigues, M., Gonçalves, S., Carneiro, D., Novais, P., Fdez-Riverola, F.: Keystrokes and clicks: measuring stress on e-learning students. In: Casillas J, Martínez-López FJ, Vicari R, De la Prieta F (eds) Management Intelligent Systems, pp. 119–126. Springer, Berlin (2013)
32. Rouvroy, A.: Privacy, data protection, and the unprecedented challenges of ambient inteligence (September 11, 2007). Studies in Ethics, Law, and Technology. Berkeley Electronic Press (2008). http://ssrn.com/abstract=1013984
33. Sanches, P., Höök, K., Vaara, E., Weymann, C., Bylund, M., Ferreira, P., Peira, N., Sjölinder, M.: Mind the body!: designing a mobile stress management application encouraging personal reflection. In: Proc. of the 8th ACM conference on designing interactive systems, ACM, pp. 47–56 (2010)
34. Schwartz, M.S., Andrasik, F.E.: Biofeedback: A Practitioner's Guide. Guilford Press, New York (2003)
35. Sridhar, M., Abraham, T., Rebello, J., D'souza, W., D'Souza, A.: Intrusion detection using keystroke dynamics. In: Proceedings of the Third International Conference on Trends in Information, Telecommunication and Computing, Springer, pp. 137–144 (2013)
36. Stucki, R.A., Urwyler, P., Rampa, L., Müri, R., Mosimann, U.P., Nef, T.: A web-based non-intrusive ambient system to measure and classify activities of daily living. J. Med. Internet Res. **16**(7), e175 (2014). doi:10.2196/jmir.3465
37. Turaga, P., Chellappa, R., Subrahmanian, V.S., Udrea, O.: Machine recognition of human activities: a survey. IEEE Trans. Circuits Syst. Video Technol. **18**(11), 1473–1488 (2008)
38. Wright, D.: The dark side of ambient intelligence. Info **7**(6), 33–51 (2005)
39. Xie, H., Zhang, M., Andreae, P.: Genetic programming for automatic stress detection in spoken english. In: Rothlauf F, Branke J, Cagnoni S, Costa E, Cotta C, Drechsler R, Lutton E, Machado P, Moore JH, Romero J, Smith GD, Squillero G, Takagi H (eds) Applications of Evolutionary Computing, pp. 460–471. Springer, Berlin (2006)
40. Zhao, J., Yuan, H., Liu, J., Xia, S.: Automatic lexical stress detection using acoustic features for computer assisted language learning. Proc APSIPA ASC, pp. 247–251 (2011)