D2.1 Strategies for activity monitoring and reasoning

Project	SWELL
Project leader	Wessel Kraaij (TNO)
Work package	2
Deliverable number	2.1
Authors	Alberto Bonomi (Philips), Muhammad Shoaib (UT), Martijn Vastenburg (UT)
Reviewers	Saskia van Dantzig, Wessel Kraaij
Date	11-03-2013
Version	1
Access Rights	PUBLIC
Status	Final

SWELL Partners:

Ericsson, NCSI, Noldus, Novay, Philips, TNO, Radboud Universiteit Nijmegen, Roessingh Research and Development, Universiteit Twente,

This publication was supported by the Dutch national program COMMIT.

Summary

As part of the COMMIT SWELL project goal of improved wellbeing at work and at home, a module for monitoring and reasoning about user activities will be developed in work package 2. This deliverable focuses on the challenges in relation to activity monitoring and reasoning, and describes strategies for activity monitoring and reasoning. The state-of-the-art is explored, and the document concludes with a proposed approach for the development activities in work package 2.

Contents

1 Introduction

In recent years, people-centric sensing and computing has received a lot of attention, mainly due to its use in healthcare and wellbeing applications [1, 2]. A key application example is health and lifestyle coaching, an application that uses various sensors to detect the user state and context, and to provide appropriate feedback to a user when needed. Such coaching can be used in different ways for different target groups who want to improve their health and lifestyle.

Physical activity plays a very important role in people's life [3, 4]. The lack of physical activity by a person can have bad influence on physical and mental wellbeing[1], thereby affecting daily life at home and work, and the quality of life in general. The importance and urgency of health and lifestyle coaching is evident from the fact that according to the Dutch Labor Inspectorate, 50% of the Dutch employees exercise too little; Dutch employees have an unhealthy lifestyle, such that 50% of them do very little exercise besides other unhealthy behaviors such as smoking, abusing alcohol, and skipping breakfast [40]. Other studies also support the argument for motivating people to be more physically active [3]**.** Therefore, there is a need for a proper health and lifestyle coaching that detects user state and context in real time and provides right motivational feedback to increase physical activity. Such coaching mechanisms can help reduce the overall cost caused by people's ill health and unhealthy lifestyle, and at the same time it can help improve wellbeing [6].

In the SWELL project [6][2], one of the key challenges is to develop mechanisms to motivate people to perform more physical activity. For example, SWELL aims to generate context-sensitive feedback messages that are relevant to the actual activities and physical location of the users. As a part of this challenge, we aim to find out how the current user state and user context can best be detected using different sensor inputs: body sensors, ambient sensors, smartphone sensors, and user reports. The goal is to collect and visualize the user state and context; in future studies this user state and context will be used to provide the right motivational feedback to the end users at the right time.

In chapter 2, the focus will be on activity monitoring and reasoning using ambient sensors, smartphone sensors and user reports. In chapter 3, the focus will be on physical state monitoring using wristband and accelerometer sensors. Chapter 4 outlines the next steps for work package 2.

[1] Wellbeing refers to how people experience the quality of their lives and includes both emotional reactions and cognitive judgments. (source: http://en.wikipedia.org/wiki/Subjective_well-being)

[2] http://www.swell-project.net

2 Activity monitoring and reasoning using a network of heterogeneous sensors

2.1 Challenges

This chapter describes the strategies for activity monitoring and reasoning for well-being application using a heterogeneous sensors network. The focus in chapter 2 is on using ambient sensors, smartphone sensors and user reports. The research challenges in view of the SWELL project context are summarized as follows:

1. How to infer user activity, situation, and state from heterogeneous and incomplete sensor data? The level of details about the user's activity, situation and state depends on the application demands and available sensing information.
2. How to make the optimal tradeoff between performance (accuracy in monitoring and inference) and energy efficiency of a system that uses such inference algorithms?
3. How and when to use different sources of information available (different sensors) at any moment of time in a complementary and cooperative way to make the inference algorithms efficient, both in terms of performance as well as energy consumption?

2.2 State of the art

Present research in activity monitoring and reasoning has targeted mainly seniors and patients with chronic conditions. The concept of knowledge workers as a target group is relatively new. Many studies have been conducted in the area of physical activity detection using sensors. A review study [3] has summarized some key projects related to smart homes, its associated technologies, and approaches in detail from 1994 till 2009. It highlights the work done, and future challenges in this area.

Many approaches with different sensing technologies to detect a user state, activity and situation have been described in publications. They can be divided into four main categories based on the type of sensors they use. A first category is the one that uses ambient sensors for user state and context detection. For example, Passive Infrared (PIR) sensors [5, 7], RFID sensors [10] and pressure sensors [11] have been used to detect physical activities in a smart home. Moreover, microphones have been used to detect physical activities in a home environment [8]. Simple state-change sensors have been used in [9] to detect physical activity with the help of supervised algorithms. A second category uses wearable sensors or body sensors to detect user's state and context, for example, Pro-move [12] and IDEEA [13]. A third category uses mobile devices for data caption (it can be considered as a sub-category of wearable sensors), for example, a smartphone with built-in accelerometers can be used to detect physical activities like walking, sitting down, and getting up [15, 16, 17, 18]. A fourth category is a hybrid approach that combines user-reports with sensed data from wearable sensors [14, 19, 20, 21]. Usually these approaches either use a rule-based mechanism or a machine-learning algorithm to detect user state and context on a data processing level [28]. Moreover, in terms of architecture, these approaches can either use centralized inference mechanisms (recognition and reasoning algorithms which runs on a single centralized device like smartphone or a desktop machine) or distributed inference mechanisms (recognition and reasoning algorithms which runs on multiple sensors in a network and work in a collaborative fashion for data processing). The use of distributed inference mechanisms is relatively new [26]. The design choices underlying these concepts depend on factors including pre-knowledge about a system, application type, available resources etc. [26, 28].

Many existing solutions tend to use wearable, smartphones and ambient sensors in isolation [16, 17, 26]. User-reports are often used in combination with wearable sensors [14, 19, 20, 21]. Each of the above-mentioned four information sources has strengths and weaknesses.

Ambient sensors generally provide a better insight into the context of a physical activity [19, 24, 25], but may not able to measure physical activities at a fine-grained level. However, they may not be able to identify who is being monitored in a home setting when there are more than one person (or a person and pets) [19, 20].

Wearable sensors can easily measure physical activities and physiological signs at a fine-grained level. But they may not be able to provide a proper context in terms of where and why some activities are happening. For example, a sitting activity in a room or at a toilet has two completely different meanings. This problem can easily be solved by using ambient sensors (sensors placed in the environment) when the number of situations is limited. Moreover, wearable sensors have some limitations: the possibility of not being worn correctly, need for great durability, battery life. Furthermore, they may be intrusive and potentially uncomfortable or unsightly [19].

Although **smartphones** can help in both recognizing physical activities and providing context, they need to be placed in a specific position on the human body because they use accelerometers-based-sensing [16, 17]. A position independent activity recognition system has been proposed for smartphones [18]. However, it is evaluated in an outdoor environment rather than in home settings. Moreover, users in a home setting may not carry the smartphone all the time with them, which makes it a partially available source of information. Moreover, women tend to not wear their smartphones on their body. For example, [39] claims that 63% of the women carry smartphones in their hang bags. However, this study only used 35 female participants for this survey.

Self-reports might be used to enhance system reasoning, when used in combination with ambient sensors, wearable sensors and/or smartphone sensors. However, the use of self-reports in such health and lifestyle coaching systems is relatively new and further studies are needed to explore its suitability in such systems. The self-reports can put some burden on users as well so self-reports should be used in a way that it doesn't annoy users.

Examples of adaptive feedback systems can be found in [12, 22, 23]. These papers demonstrate how the user context can be used to adjust the feedback to the actual context of use.

State-of-the-art systems combine data from ambient sensors, wearable sensors, smartphones and self-reports. For example, data from ambient sensors and wearable sensors has been combined using fusion techniques to complement each other and improve physical activity detection [24, 25]. Improvements in detection performance have been reported compared to use of a single data source. This shows a potential for using different sources of information in a complementary way to provide better detection of user state and context and right motivational feedback. Though research is going on to combine different information sources for better understanding of a user activity and context (state and situation), only few studies have been conducted on understanding user state and context in relation to context-dependent motivational feedback. Further research is needed to investigate the context-dependent motivational feedback in relation with the user state and context, which might lead to an improved wellbeing if provided at right moments and situations.

2.3 Strategies

The strategies for activity monitoring and reasoning using a network of heterogeneous sensors can be described on two levels. These levels are sensing or data collection level (lower level) and data processing level (higher level). The sensing level refers to the actual sensors and how they report events or provide data to a higher level. The data processing level refers to the actual processing done on the reported data by sensing level. The strategies for these two levels are described in the next sub-sections.

2.3.1 Strategies on a data collection level

The following three strategies deal with how different sensors are used by well-being applications.

Strategy Sense-PSC: Sensing based on pre-defined sensor configuration

In strategy Sense-PSC, the configuration of sensors is predefined. The data processing algorithms are developed for a specific static configuration of sensors [30, 31]. These characteristics make this strategy easy to design and implement [31]. For example, when a fixed number of PIR sensors are installed in a home and activity recognition algorithms are developed for such a static network, it is basically using this strategy. It has been used in [5, 7, 8, 12, 13, 15, 16]. The alternative to this strategy is opportunistic sensing.

Strategy Sense-OS: Opportunistic Sensing

In strategy Sense-OS, the configuration of the sensor network is not known in advance. The algorithms do not rely on static sensor network deployment [30]. Different types and numbers of sensors are used as they become available. It is more flexible or open minded in terms of providing different information for different applications than strategy Sense-PSC. However, it is generally difficult to design and implement this strategy as compared to strategy PSC [30, 31].

Strategy Sense-POS: Partial Opportunistic Sensing

Strategy Sense-POS combines strategies Sense-PSC and Sense-OS in a hybrid and dynamic way. The optimal strategy is selected in run time based on different situations and conditions as per application demands and available sensing sources. For example in a home setting, a system can use smartphone sensors for activity recognition as main source of information but if they become unavailable temporarily due to some reason, this system can use sensors in the user's home environment in order to work properly.

The next two strategies define how a single or multiple sources of information is used by data processing level. These two can be regarded as pre-data processing level strategies.

Strategy Sense-NDF: No data fusion

In strategy Sense-NDF, sensor data from different sensors is considered in isolation, without data fusion. In other words, a system or application relies only on one ambient sensor (PIR sensors, or pressure sensors, or microphones etc.) [e.g., 5, 7, 8], or one smartphone sensor (accelerometer) [16, 17, 18].

Strategy Sense-DF: Data fusion

In strategy Sense-DF, a combination of two or more sensing sources is used in a cooperative way to complement each other and improve the activity monitoring and reasoning process in well-being applications (using data fusion techniques). For example, using smartphones in combination with ambient sensors or smartphones in combination with body sensors or self-reports. Moreover, different smartphone sensors (accelerometer, magnetometer, and GPS) can also be used for data fusion to improve overall reasoning process. There can be many such hybrid combinations depending on the user scenarios and application demands. Data fusion techniques are used for a combination of ambient and wearable sensors in [24, 25] to detect physical activities. Moreover, [38] uses data fusion techniques for different smartphone sensors.

2.3.2 Strategies on data processing level

There are two different clusters of strategies on data processing level: one level regards *where* the data is processed, and the other level regards *how* the data is processed.

Strategy Process-CDP: Centralized data processing

This strategy is about processing sensor data in a centralized fashion, i.e., at one central node. This processing node can be a dedicated powerful sensor node, a smartphone, or a desktop machine etc. For example, centralized approach is used in [5, 7, 15, 16].

Strategy Process-DDP: Distributed data processing

This strategy is about processing sensor data at multiple nodes in a sensor network. It can be done in a completely distributed way where each node process the data and then a voting mechanism is applied or in partially distributed way, where some processing is done on all nodes and final processing is done by a centralized node. It has been used in [26]. It is a relatively new approach for activity recognition and reasons using heterogeneous sensors network [2].

The following are strategies on how to process data irrespective of processing location. There are mainly two types of mechanism used, depending on application types.

Strategy Process-RB: Rule-based mechanisms

Rule-based mechanisms are used for situations where pre-knowledge about system is available, and where the rules can be defined in a declarative fashion. In such mechanisms, simple actions are defined in an if-else fashion where these pre-defined actions are performed when certain events occur. For example, a wheelchair coach for disabled people uses a rule-based mechanism to process data or make decisions [2] because there is enough pre-knowledge available about such a simple system (wheel chair).

Strategy Process-ML: Machine-learning mechanisms

Machine-learning is a more generic approach and can be used for both simple and complex situations [28]. It is most commonly used approach to process sensors data in wellbeing applications

[26, 28]. Such machine learning mechanisms can further be classified into supervised, unsupervised and semi-supervised mechanisms. It depends on different factors like sensor data type and application demands to decide which type of mechanisms to use in a specific situation. Some examples of machine learning techniques used in activity recognition are decision trees, nearest neighbor and Bayesian Networks, support vector machines, neural networks, and Markov chains [18].

2.4 Proposed strategy in SWELL project

The choice of strategy for the SWELL project depends on many factors [26, 28], including the application type, the available sensing resources, and pre-knowledge about the system. Different combinations will be implemented and evaluated in order to find the optimal solution for different settings.

As a first step in SWELL project, activity recognition algorithms will be developed for a simple smartphone application which keeps track of the user's activities (walking, running, biking, eating, riding in a vehicle, climbing upstairs and downstairs, and inactive states e.g. standing and sitting) and activity level (in terms active time or energy consumption) using only smartphone sensors (accelerometer, magnetometer, gyroscope, microphone, GPS etc.). Based on the nature of this application, a combination of strategy Sense-PSC and Sense-DF will be used on sensing level and a combination of strategy Process-CDP and Process-ML on data processing level as these strategies suits this application better. The primary goal of the first phase is to explore the value of the different strategies in the context of the SWELL project.

As a next step, the activity recognition module will be integrated in the demonstrators and/or prototypes that are being developed in SWELL work packages 5 and 6. The functional requirements will be defined based on the outcome of the exploration phase and the requirements from work packages 5 and 6. <*sentence removed / confidential*> In this case, a combination of strategy Sense-POS and Sense-DF will be used on sensing level whereas the strategies on data processing level will remain the same. In summary, these strategies can be tried in different combinations as per application demands and available sensing resources for better performance. The general overview of an activity monitoring and reasoning solution is visualized as follows in Figure 1 in terms of sensing sources and data processing approach.

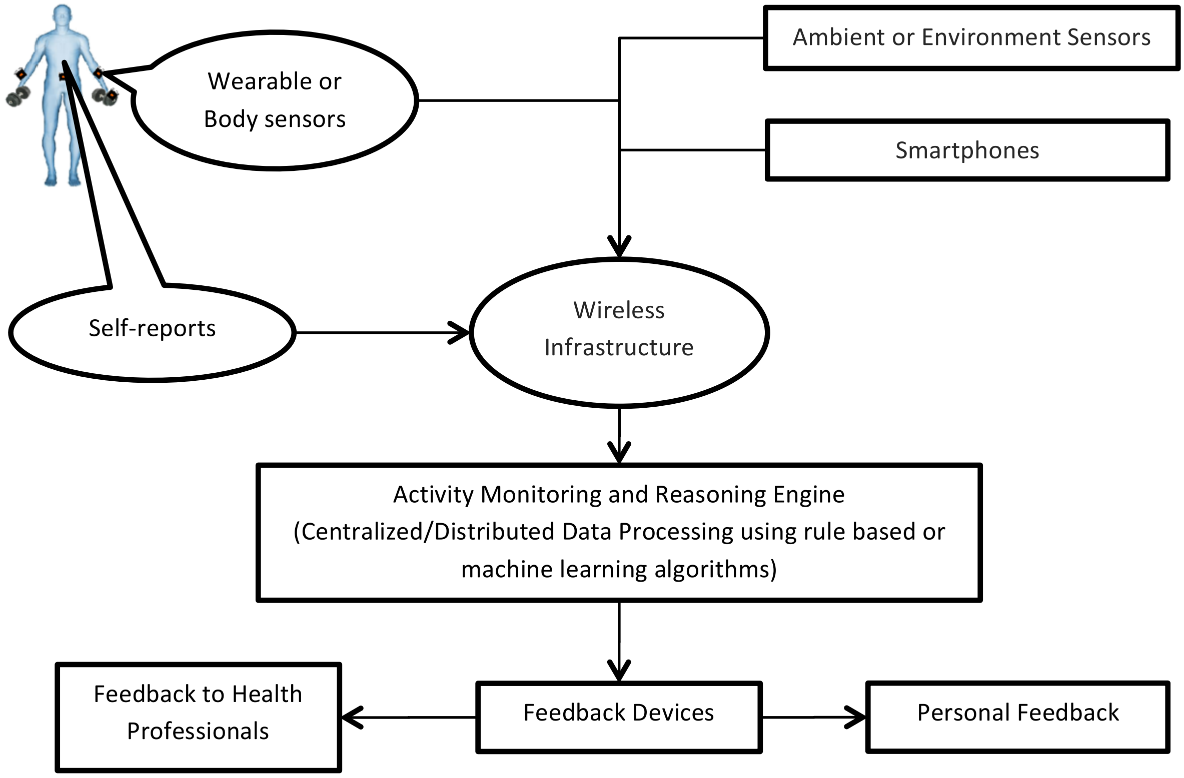

Figure 1. Schematic representation of the proposed strategy for activity monitoring and reasoning.

3 Physical state monitoring using wrist-band heart-rate monitoring & accelerometry

3.1 Challenges

- confidential -

3.2 State of the art

- confidential -

3.3 Proposed strategy

- confidential-

4 Next steps

This document has presented state of the art and strategies for activity monitoring. For the SWELL project, the activity monitoring algorithms will be developed in several iterations.

In the first iteration, basic algorithms will be developed for the smartphone and for wristband activity recognition. The smartphone application will keep track of user activities, state and situation using only smartphone sensors (accelerometer, magnetometer, gyroscope, microphone and GPS); the wristband application will focus on detection, extraction and assessment based on accelerometer data. In a controlled setting, the algorithms will be validated in order to be able to provide a proper baseline for future field studies.

Whereas the activity recognition algorithms for the smartphone and wristband are initially developed stand-alone, there is a huge potential in combining both devices. For example, wristband-based classification could be improved by using context information from a smartphone application. The potential synergies will be studied directly after the stand-alone explorations in phase 1.

As a next step, the basic algorithms will be integrated in prototypes and proof-of-concepts for WP5 (Smart wellbeing applications for lifestyle changes) and WP6 (smart wellbeing applications for flexible working). In close consultation with these work packages, the algorithms will be iteratively further developed.

Moreover, the algorithms will be integrated in the golden demo, an integrated demonstrator for the SWELL project. The golden demo will be defined in 2013-Q1/Q2, and will be improved in cycles.

References

1. Campbell A.T., Eisenman S.B., Lane, N.D., Miluzzo, E., Peterson, R.A., Lu, H., Zheng, X., Musolesi, M., Fodor, K., Ahn, G. (2008) *The Rise of People-Centric Sensing*, In IEEE Internet Computing, vol. 12, no. 4, pp. 12-21.

2. Marin-Perianu, R.S., Jimenez Garcia, J.C., Bosch, S., Marin-Perianu, M., Havinga, P.J.M. (2012) *Managing Chronic Conditions Using Wireless Sensor Networks*. In: Handbook of Ambient Assisted Living: Technology for Healthcare, Rehabilitation and Well-being. Ambient Intelligence and Smart Environments 11. IOS Press, Amsterdam, pp. 626-639. ISSN 1875-4163 ISBN 978-1-60750-836-6

3. Chan, M., Campo, E., Estève, D, Fourniols, J.Y. (2009) *Smart homes current features and future perspectives.* Maturitas 2009 Oct 20, 64(2), 90-7.

4. Bosems, S. *A ubiquitous system for smart reasoning for well-being at home and at work*. Pervasive Computing and Communications Workshops (PERCOM Workshops), 2012 IEEE International Conference on. IEEE, 2012.

5. Le, X.H.B., Di Mascolo, M., Gouin, A., Noury, N. (2008). *Health Smart Home for elders-A tool for automatic recognition of activities of daily living.* In Engineering in Medicine and Biology Society. EMBS 2008. 30th Annual International Conference of the IEEE (pp. 3316-3319).

6. Kraaij, W. *COMMIT Projectplan, Workpackages, Deliverables, Budget User Centric Reasoning for Well-working (P07)*. TNO, Project planning, 2011.

7. Banerjee, S., Steenkeste, F., Couturier, P., Debray, M., Franco, A. (2003) *Telesurveillance of elderly patients by use of passive infra-red sensors in a 'smart'room*. Journal of telemedicine and telecare, 9(1), 23-29.

8. Fleury, A., Noury, N., Vacher, M., Glasson, H., Seri, J.F. (2008) *Sound and speech detection and classification in a health smart home.* In Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE (pp. 4644-4647). IEEE.

9. Tapia, E., Intille, S., Larson, K. (2004) *Activity recognition in the home using simple and ubiquitous sensors.* Pervasive Computing, 158-175.

10. Hsu, J.M., Wu, W.J., Chang, I.R. (2007) *Ubiquitous multimedia information delivering service for smart home*. In Multimedia and Ubiquitous Engineering, 2007. MUE'07, pp. 341-346.

11. Lim, J.H., Jang, H., Jang, J., & Park, S.J. (2008). *Daily activity recognition system for the elderly using pressure sensors.* In Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE, pp. 5188-5191.

12. op den Akker, H., Jones, V.M., Moualed, L.S., Hermens, H.J. (2012) *A Context-Aware Adaptive Feedback Agent for Activity Monitoring and Coaching.* In Proceedings of Measuring Behavior 2012, 8th International Conference on Methods and Techniques in Behavioral Research, Utrecht, The Netherlands, August 2012

13. Zhang, K., Werner, P., Sun, M., Pi-Sunyer, F.X., Boozer, C.N. (2012). *Measurement of human daily physical activity.* Obesity Research, 11(1), 33-40.

14. Vastenburg, M.H., Romero, N. (2011) *Experience Tags: Enriching Sensor Data in an Awareness Display for Family Caregivers.* In: D. Keyson and B. Kröse (Eds.): AmI 2011, LNCS 7040. Springer-Verlag Berlin Heidelberg: 285-289.

15. Lau, Sian Lun, Konig, I., David, K., Parandian, B., Carius-Düssel, C., Schultz, M. (2010) *Supporting patient monitoring using activity recognition with a smartphone*. In 7th International Symposium on Wireless Communication Systems (ISWCS), 2010, pp. 810-814.

16. Hache, G., Lemaire, E.D., Baddour, N. (2010) *Mobility change-of-state detection using a smartphone-based approach*. In 2010 IEEE International Workshop on Medical Measurements and Applications Proceedings (MeMeA), pp. 43-46.

17. Zhang, S., McCullagh, P., Nugent, C., Zheng, H. (2010) *Activity Monitoring Using a Smartphone's Accelerometer with Hierarchical Classification*. In 2010 Sixth International Conference on Intelligent Environments (IE), pp. 158-163.

18. Khan, A.M., Lee, Y.-K., Lee, S.Y., Kim T.-S. (2010) *Human activity recognition via an accelerometer-enabled-smartphone using kernel discriminant analysis*. In 2010 5th International Conference on Future Information Technology (FutureTech), pp. 1-6.

19. Mann, W.C., Milton, B.R. (2005) *Home automation and smart homes to support independence*. Smart technology for aging, disability, and independence: The state of the science: 32-66.

20. van Kasteren, T. (2011) *Activity Recognition for Health Monitoring Elderly using Temporal Probabilistic Models*. PhD thesis, Universiteit van Amsterdam

21. Jimenez, J., Romero, N.A., Keyson, D. (2011) *Capturing patients' daily life experiences after Total Hip Replacement*. In 2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), pp. 226-229.

22. Wieringa, W., op den Akker, H, Jones, V.M., op den Akker, R., Hermens, H. (2011) *Ontology-Based Generation of Dynamic Feedback on Physical Activity.* In: Proceedings of the 13th Conference on Artificial Intelligence in Medicine (AIME), pp. 55-59.

23. op den Akker, H., Hermens, H.J., Jones, V.M. (2011) *A Context-Aware Adaptive Feedback System for Activity Monitoring.* In: in Book of Abstracts of ICAMPAM 2011, the 2nd International Conference on Ambulatory Monitoring of Physical Activity and Movement, May 2011, Glasgow, United Kingdom

24. Atallah, L.M. ElHelw, Pansiot, J., Stoyanov, D., Wang, L., Lo, B., Yang, G.Z. (2007) *Behaviour profiling with ambient and wearable sensing.* In 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007), pp. 133-138.

25. Pansiot, J., Stoyanov, D., McIlwraith, D., Lo, B., Yang, G. (2007) *Ambient and wearable sensor fusion for activity recognition in healthcare monitoring systems.* In 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007), pp. 208-212.

26. Atallah, L., McIlwraith, D., Thiemjarus, S., Lo, B., Yang, G.-Z. (2012) *Distributed inferencing with ambient and wearable sensors*. Wireless Communications and Mobile Computing 12, no. 1 (2012): 117-131.

27. Patel, Shyamal, Park, H., Bonato, P., Chan, L., Rodgers, M. (2012) *A review of wearable sensors and systems with application in rehabilitation.* J Neuroeng Rehabil 9 (2012): 21.

28. Siewiorek, D., Smailagic, A., Dey, A. (2012) *Architecture and Applications of Virtual Coaches*. Proceedings of the IEEE 100, no. 8 (2012): 2472-2488.

29. http://www.who.int/dietphysicalactivity/pa/en/index.html [Last accessed on 11 Dec. 2012]

30. Kapadia, A., Triandopoulos, N., Cornelius, C., Peebles, D., Kotz, D. (2008) *AnonySense: Opportunistic and privacy-preserving context collection.* Pervasive Computing: 280-297.

31. Tavenard, R., Onkar Ambekar, E., Pauwels, J., Waaijers, M. (2007) *Opportunistic Sensing and Learning in Sensor Networks.* In Content-Based Multimedia Indexing, 2007. CBMI'07. International Workshop on, pp. 46-52.

32. Zhang, K., Werner, P., Sun, M., Pi-Sunyer, F.X., Boozer, C.N. (2003) *Measurement of human daily physical activity*. Obes Res 2003; 11: 33–40.

33. Bussmann, J.B., Martens, W.L., Tulen, J.H., Schasfoort, F.C., van den Berg-Emons, H.J., Stam, H.J. (1996) *Measuring daily behavior using ambulatory accelerometry: the activity monitor.* Behav Res Methods Instrum Comput 2001; 33: 349–356.

34. Pober, D.M., Staudenmayer, J., Raphael, C., Freedson, P.S. (2006) *Development of novel techniques to classify physical activity mode using accelerometers*. Med Sci Sports Exerc 2006; 38: 1626–1634.

35. Bonomi, A.G., Goris, A.H., Yin, B., Westerterp, K.R. (2009) *Detection of type, duration, and intensity of physical activity using an accelerometer.* Med Sci Sports Exerc 2009; 41: 1770–1777.

36. Zhang, K., Werner, P., Sun, M., Pi-Sunyer, F.X., Boozer, C.N. (2003) *Measurement of human daily physical activity*. Obes Res 2003; 11: 33–40.

37. Preece, S.J., Goulermas, J.Y., Kenney, L.P.J., Howard, D., Meijer, K., Crompton, R (2009) *Activity identification using body-mounted sensors—a review of classification techniques.* Physiol. Meas. 2009; 30.

38. Ganti, R.K., Srinivasan, S., Gacic, A. (2010) *Multisensor fusion in smartphones for lifestyle monitoring*. In Body Sensor Networks (BSN), 2010 International Conference on, pp. 36-43.

39. Breitinger, F., Nickel, C. (2010) *User survey on phone security and usage.* In Gesellschaft für Informatik (GI), p. 139

40. Hooftman, W., Klein Hesselink, J., van Genabeek, J., et al. (2011) *Kwaliteit van de arbeid, effecten en maatregelen in Nederland*. TNO, Ministerie van Sociale Zaken en Werkgelegenheid