Online Physical Activity Monitoring From Head Kinematics

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***Abstract*—With older age, people experience increasing hearing loss. With the use of assistive technology systems it is possible to preserve and improve the quality of life of elderly people with hearing losses. The Augmented Hearing Experience and Assistance for Daily life (AHEAD) system, composed of hearing glasses (augmented with Bluetooth audio communication, and physiological sensors) wirelessly connected to a mobile phone also connected to a smart home environment platform, allows to provide services on top of the hearing enhancement provided by the hearing glasses. Beside the health related services that the AHEAD system offers (heart rate monitoring, emergency alarms), a physical activity assistant has been identified to be relevant in order to reduce sedentary behaviours. In this paper, we investigated how accurate fitness algorithms (walking time, step counter, physically active/inactive periods) based on head kinematic data would be. For that purpose we have adapted state-of-the art algorithms. A total of 10 healthy users performed activities of daily living and walking sessions. The results show that the head location is suitable to detect fitness indicators but some personalization of some parameters would be needed to improve the performance of the detection methods.**

Keywords–Active Ageing; Head Kinematics; Walking Detection; Hearing Instrument; mHealth.

I. INTRODUCTION

With older age, people experience increasing hearing loss. With the use of assistive technology systems it is possible to preserve and improve the quality of life of elderly people with hearing loss. Currently few hearing aids have a wireless connectivity and for those which support it, it is done through a dedicated physical device which works as a gateway between the hearing aid and the smartphone (Starkey SurfLink Mobile 2 (Starkey, 2015), Phonak ComPilot (Phonak, 2015)). The low usability of such wireless solutions limits the services that can be delivered to the hearing impaired person. The European project Augmented Hearing Experience and Assistance for Daily life (AHEAD) aims to provide a speech-controlled assistive system that supports elderly people in their everyday life as communication tool and healthcare manager, e.g., initiating phone calls, recording vital parameters, performing a audio verification test from home and providing environmental information. The AHEAD system is integrated into hearing glasses that are a combination of traditional hearing aids and eye glasses: two devices elderly people are used to and have accepted already. As health management is especially important for elderly people, the modified hearing aid is able to measure vital signs such as heart rate and body core temperature through sensors that are in contact with the skin of the inner ear and transmit these data for further analysis helping elderly people in self-managing their health. Finally, a 3D inertial sensor embedded into the hearing glasses records the user's physical activity in order to reduce sedentary behaviours. The AHEAD assistant is wirelessly connected to a smart phone which is the gateway to the smart living environment and third party services.

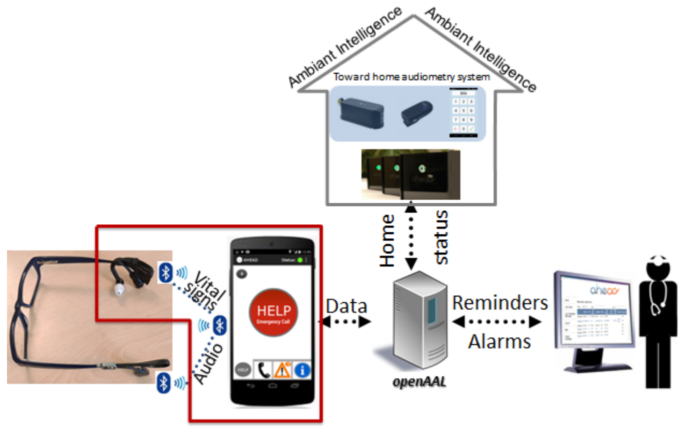

Figure 1. Overall AHEAD components

Figure 1, depicts the AHEAD system composed by the openAAL platform (back-end and ontology platform), a smartphone, a hearing instrument (either eyeglasses or behind the hear system), hearing verification tools, and embedded physiological and kinematic sensors. For more details regarding the hardware and the services offered, please refer to Barralon [1].

In this paper, we are focusing on a sub part of the AHEAD which is the smartphone and the head mounted physiological and kinematic sensor (red polygon on Figure 1), which are the key components supporting the AHEAD fitness service. This service monitors and provides feedback/recommendation to the user about his/her daily walking time, number of steps and also the duration of physically active and inactive periods with the final goal to reduce the amount of inactivity. This service was considered important within the AHEAD system because the relationship between greater time spent in sedentary behavior and the presence of Activity of Daily Living (ADL) disability has been reported for older adults [2].

Even though they are commercial activity monitors (FitBit, Polar, ActiGraph, Tritrac RT3, Actical, the Actiheart, Activ8) [3] available on the market the AHEAD consortium decided, based on collected user requirements [4], not to add any another body sensor (e.g., watch) to promote physical activities but rather investigate and use the sensor embedded into the hearing glasses. In this case a 3D accelerometer already integrated into the Cosinuss device [5]. The question was, however to investigate whether the head was a suitable location for detecting walking events. It is known that the head vertical position is very well regulated during walking in order to maximise the visual input quality [6]. Brajick [7] investigated

 ISBN: 978-1-61208-565-4

different smartphone locations (hand held, backpack, handbag, trousers back pocket, trouser front pocket, and handheld using). They, obviously, did not study the head location.

Since the AHEAD smartphone is the gateway between the hearing glasses (microphone, speaker, physiological sensors) and the back-end platform (openAAL) we have investigated which are the available algorithms supporting the detection of walking events, the calculation of the daily number of step and the duration of physically active and inactive periods with low computation power. We have found the Jigsaw Continuous Sensing Engine for Mobile Phone Applications [8] from which we adapted the method to track the amount of physically active and inactive events. We have used the frequential Short Time Fourier Transform (STFT) method proposed by Barralon [9] and confirmed by Brajick [7] to be better than other alternatives such as thresholding time series (acceleration magnitude, acceleration energy, mean crossing counts, etc.). For reference, the following papers estimate walking detection event but also gait authentication and identification [10] [11], stride and heading determination for pedestrian navigation system [12], and gait event detection for Functional Electrical Stimulation (FES) actuation [13]. Recently, a novel confidence-based multiclass boosting algorithm for mobile physical activity monitoring has been proposed by Reiss [14] to improve the classification performance on most of the evaluated datasets, especially for larger and more complex classification tasks.

Since the AHEAD system includes a smartphone anyway, we have selected four mobile applications (Pedometer, WalkLogger, Pacer, Google Fit) to compare our results with.

The rest of the paper is structured as follows. Section 2 describes the materials and methods offering the aforementioned services. Section 3 reports on the performance achieved by the system in comparison with other applications. Conclusions are drawn in the Section 4.

II. Measurements and Methods

A user experiment was performed in Tecnalia HomeLab, to test the accuracy of the AHEAD fitness algorithm (including walking time, number of steps and active/inactive duration), and compare with other commercially available Android apps.

A. Subjects

10 Healthy subjects were involved in the test, all Tecnalia employees (5 males, 5 females; 25-64 years old, mean 35.8 years, standard deviation 11.3 years).

B. Experimental protocol

In order to test the sensitivity (Se) and specificity (Sp) of both the Active/inactive and Walking/non Walking detection methods the users were asked to perform the following activities during the test:

1) Spending 2 minutes in sitting position reading the newspaper (in this situation the user should be detected as ”inactive” and ”non walking”).
2) Standing up and arranging the kitchen during 3 minutes (should be detected as ”active”. The evaluation of the performance (e.g Se, Sp) of the walking detection algorithm was never performed on this part of the recording since some few and sporadic steps happened and were not counted by the experimenters because of the complexity to define what is a step in this context).
3) Standing up and still standing for 2 minutes watching a video on TV (should be detected as ”inactive” and ”non walking”).
4) Sitting down and remaining sited for 4 minutes watching a video on TV (should be detected as ”inactive” and ”non walking”).
5) Initiating gait and walking for 5 minutes (should be detected as ”active” and ”walking”). In this phase the number of steps performed by the users was counted and reported by two observers.

C. Materials

1) Hardware: For this experimentation we used a Nexus 5 smartphone [15] running an Android operating system (version 5.1, released on December 2014. API 22). The Nexus 5 is powered by a 2.26 GHz quad-core Snapdragon 800 processor with 2 GB of RAM. The smartphone was connected to a Cosinuss One device [5] in charge of measuring physiological parameters (e.g., heart rate, oxygen saturation, body surface temperature) but also the head motion using a 3-axis accelerometer. The component is an integrated circuit which records an analog accelerometric input and returns a digital signal with 12 bits resolution. The sampling rate was set to $100Hz$. The accelerometer data (packet of the five last measurements) was sent by Bluetooth Low Energy (BLE), RAW Data Service (UUID 0xA000), RAW Data characteristic (UUID 0xA001), every 50ms to the Nexus 5.

2) Software: During all the trials, five mobile applications were running in parallel and recoding the tasks.

- AHEAD app: This app has been developed by Tecnalia within AHEAD project. It provides different services as already explained above. One of the services provided by AHEAD app is the Fitness service, that is being analysed in this publication. It monitors and provides feedback to the user about his/her daily walking time, number of steps and also the duration of physically active and inactive periods. The algorithms estimating these variables are analysed in the next section. The Fitness service is connected by BLE to Cosinuss One device, and receives x and y axes accelerometer data in the RAW Data Service every 50ms, including 5 x and 5 y axis data per package. This data is buffered, and then analysed in a period of 1 second. So, updated information about active/inactive time, walking time and number of steps is provided every 1 second.
- Pedometer (tayutau) [16]
- WalkLogger pedometer [17]
- Pacer [18]
- Google Fit [19]

D. Detection and classification methods

The first version of fitness algorithms have been developed in Matlab. This first development was validated in [9]. To implement these algorithms in AHEAD, we translated them into Java. Due to the processing limitation of a smartphone compared with a computer, and the fact that other AHEAD services are concurrently running in parallel in the smart phone, a loss in the algorithm performance could be considered. We therefore compared on pre-trial data the Matlab and Android outputs (Figure 3 and Figure 4).

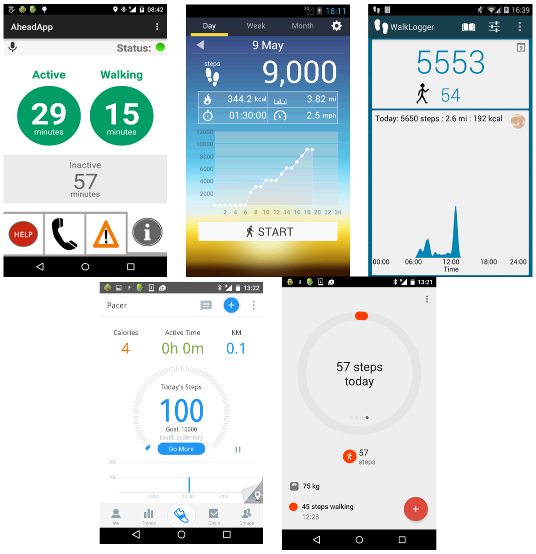

Figure 2. AHEAD app (top left) ; Pedometer (top center) ; WalkLogger (top right) ; Pacer (bottom left) ; Google fit (bottom right)

In a second step we have compared the AHEAD app methods with other Android apps. However, some of the selected apps (Google Fit, Pacer) do not detect (at least display) the physically active (or inactive) periods. For example when the user is not walking but still performing an activity of daily living (e.g., cleaning the dishes) no information is shown. In AHEAD these active periods are also detected and counted, with the aim to reduce the amount of inactivity of the user.

1) Physically active or inactive: In order to detect whether the user is physically active or not we have followed the approach of Lu and collaborators [8]. A stationary state detector is used to select qualified $\overrightarrow{a_i} = (a_{x,i}, a_{y,i}, a_{z,i})$ (i.e.,stationary accelerometer readings). Our stationary detector begins by dividing raw data into candidate frames each contain M successive samples. For each frame, the mean and standard deviation are calculated for the three axes. If all three standard deviations fall below a percentage threshold σ of the mean, we assume the device is stationary. In the AHEAD case and in order to alleviate the communication bandwidth between the mobile and the hearing glasses, we stream only two dimensions of the accelerometric components (vertical (a_v) and antero-posterior (a_{AP})). Instead of applying a threshold on each standard deviation of each component [8], we rather calculate the acceleration magnitude (AM) $AM_i = \sqrt{(a_{AP,i}^2 + a_{v,i}^2)}$ of the candidate frame and apply a threshold (named *minVariation*) on the standard deviation of the AM. The length of the candidate frame was set to one second (100 samples).

2) Walking duration and number of steps: Recently Brajdic has reported a comparison of different walking detection algorithms (MAGN_TH, ENER_TH, STD_TH, NASC+STD_TH, STFT, CWT, DWT, HMM) [7]. His conclusion was that the best performing algorithms for walk detection were the two thresholds based on the standard deviation (STD_TH) and the signal energy (ENER_TH), STFT and NASC, all of which exhibited similar error medians and spreads.

As explained in Barralon [9] and Brajdic [7], the walking detection is performed as follows: signal was split into successive time windows using SFTF of size *DFTwin* and labelled as walking if it contained significant (greater than a threshold: *DFTthresh*) spectral energy at typical walking frequencies *freqwalk*.

For the *DFTthresh* threshold, we used what was proposed by Barralon [9]:

$$DFTthresh = \frac{1}{pFactor}\left[\frac{b.DFTwin}{2}\right]^2 \qquad (1)$$

where $pFactor$ is an attenuation coefficient, b the amplitude of the input signal (a_V or a_{AP}).

However, since the value of *DFTthresh* is adapted according to the amplitude b of the input signal, a noise with a small amplitude can be classified as walk if its frequency content is included within the frequency range of interest. To overcome this problem, Barralon [9] defined a constant threshold (T_b, named *minAmp* in this paper) to test b. If the amplitude of the input acceleration is too low then the algorithm will never classified the candidate frame as ”walking”.

The step counting is then only computed when walking has been detected and we compute a fractional number of strides for each window by dividing the window width by the dominant walking period it detected. These fractional values were then summed to estimate the total number of step taken.

During daily life activities, the fastest body movements occur when walking which corresponds to accelerometric signal ranging from 0.6 Hz to 2.5 Hz [20]. However Brajdic [7] has extended it to [0.01-7] Hz for the Short Term Fourier Transform (STFT) method.

For the walking and active/inactive detections we used the following parameters (see section III-B):

- $pFactor = 0.03$
- $frequalk = [0.8 - 5]Hz$
- input accelerometer axis: vertical
- $minAmp = 0.1g$
- $minVariation = 0.13g$

III. Results

A. AHEAD algorithm - Comparison between Matlab and Smartphone

In figures 3 and 4 the results of the comparison between fitness algorithms running in Matlab and in AHEAD app are shown. Figure 3 shows the results during activities of daily living (e.g., cleaning up the kitchen table) and inactive episodes (reading and watching TV). Minor differences can be identified between the two implementations, surely due to the mislaid of some accelerometer data packages. Figure 4 shows the results of a walking sequence, where the results are the same for both Matlab and Android algorithms of walking detection and active/inactive detection. Step counting has not been included in this Matlab vs smartphone comparison, because it requires very few processing resources; the key point to correctly count the steps is the correct detection of walking episodes.

B. Thresholds identification

As presented in section II-D, several parameters have to be defined to detect the user activity. Even if values of these parameters have been reported for trunk mounted devices in various publications [9][7], we investigated how the change of some of them impact the performance for head mounted device which is the case of the AHEAD solution.

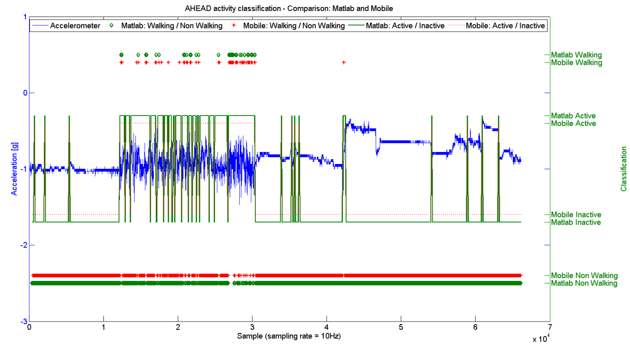

Figure 3. Illustration of AHEAD classification (walking/non walking, active/inactive) durind daily life activities

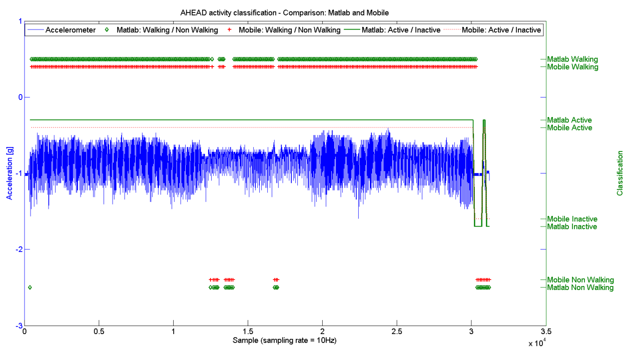

Figure 4. Illustration of AHEAD classification (walking/non walking, active/inactive) durind a walking sequence

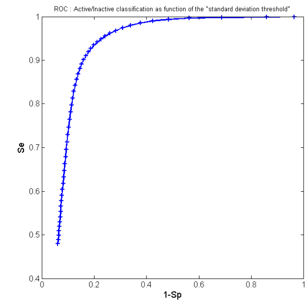

Figure 5. Active/inactive ROC curve as a function of the $minVariation$ parameter

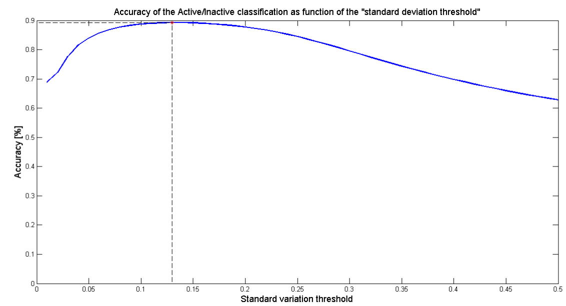

Figure 6. Active/inactive accuracy as a function of the $minVariation$ parameter

In total, 10 subjects have performed the trial. Data from the first 3 subjects has been used to study and select the inner thresholds/values of the algorithms. The other 7 subjects' data has been used to validate the algorithm. The first three users have been selected to be representative of the whole set of subjects, and so we tried to include variation in gender and age: 2 males, 1 female; mean age 42.7 years, standard deviation of age 19.8 years.

1) Active/Inactive: The threshold to identify in the active/inactive detection algorithm is the threshold *minVariation* to which the standard deviations are compared with. Figures 5 and 6 show the results of this identification, with the Receiver operating characteristic (ROC) curve and the maximum accuracy with different threshold *minVariation* values. The best accuracy of 89% was obtained for $minVariation = 0.13$.

In the threshold identification process, data from tasks 1, 3 and 4 (sitting or still reading or watching TV) were tagged as inactive, and data from tasks 2 and 5 (arranging the kitchen and walking) were tagged as active.

2) Walking: Walking detection algorithm has three parameters that can be adjusted (and will affect the sensitivity and specificity). We therefore tested several combinations of those three parameters and analysed how they affect the performance of the walking detection algorithm:

- Walking detection algorithm is based on acc data from only one axis. So, the best axis (V or AP) to be used should be defined. V is the vertical axis, and AP is the anteroposterior axis.
- The highest peak on frequencies between 0.8Hz and 5.0Hz should be bigger than a percentage of the theoretical maximum frequency. This attenuation coefficient *pfactor* (1) should be defined.
- The amplitude of the acc signal above the mean should be bigger than a threshold *minAmp* to be defined (see section II-D2).

Figures 7 and 8 show the results of the identification of these 3 parameters. When selecting these values, a better sensitivity has been prioritized at the expense of poorer specificity. The best results were obtained for the vertical axis. We selected an attenuation coefficient $pFactor = 0.03$ and the minimum amplitude of the acc signal above the mean $minAmp = 0.1$.

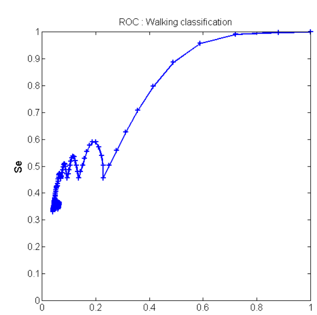

Figure 7. Learning: Walking - ROC as function of $pFactor$, $minAmp$ and acceleration axis (V or AP).

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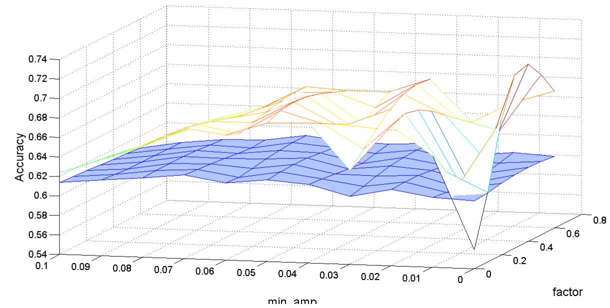

Figure 8. Learning: Walking Accuracy as function of $pFactor$, $minAmp$, and $axis$. The blue plot represents the AP axis and the white one the V axis

For this threshold identification process, data from tasks 1, 3 and 4 (sitting or still reading or watching TV) were tagged as non walking, and data from task 5 (walking) was tagged as walking. Data from task 2 was excluded from this section, because some few and sporadic steps happened and were not counted by the experimenters because of the complexity to define what is a step in this context.

C. Results on seven subjects

After setting the required parameters (see previous section), the configured algorithms were validated with the remaining 7 users: 3 males, 4 females; mean age 32.9 years (standard deviation 5.3 years).

Table I shows the overall results of the test, comparing AHEAD fitness service with the true values and the results obtained with other Android apps available in Google Play.

- Active/Inactive time detection algorithm has a sensitivity of 89 percent.
- Walking time algorithm has a sensitivity of 86 percent for all 7 users. For the 4 users where the algorithm has a better performance, the sensitivity is 96 percent, while it is of 72 percent for the other 3 users.
- Step counter has also a sensitivity of 86 percent for all 7 users. For the 4 users where the algorithm has a better performance, the sensitivity is 93 percent, while it is of 77 percent for the other 3 users.

In Figures 9 and 10, the walking time and number of steps information is shown. Numbers correspond to average values of the 7 users, and associated standard deviation in brackets.

AHEAD walking detection and step counting algorithms clearly had much worse performance with 3 of these 7 users. In Table I and in Figures 9 and 10, new columns were added to distinguish the algorithms good performance in 4 users and bad performance in 3 users.

IV. Conclusion

A new approach for fitness activity detection has been presented in this paper. The main novelties presented here are 1) the head location of the accelerometer sensor embedded into a pair of hearing glasses, and 2) the detection of physically active episodes that do not necessary imply a walking event. The integration of additional sensors into the hearing instruments will facilitate the user acceptance while offering additional services with the aim to increase the autonomy level of the users and reduce the amount of sedentary behaviours.

The results presented support that the head kinematics is a suitable location for physical activity monitoring. The results are promising, with a sensitivity higher than 85% for all 3 algorithms (active detection, walking detection and step counter). Even though the user trial was designed to cover sequentially inactive, active, and walking phases, the test was performed in a Homelab and the users executed those tasks in a very natural manner. As a consequence, sequences that were supposed to be ”inactive” sometimes include ”active” events (postural re-adjustment on a chair, head and trunk motion to scratch a leg, ...). Similarly, during walking we observed large head movements to either look around or talk to the experimenter. Besides, the Cosinuss sensor was placed by the user him/herself on the hear, and therefore the sensor placement was not identical for all users. All these elements contributed to reduce the performance of the implemented algorithms. The raw acc data of the 3 users with worse walking detection performance show some similarities, e.g., changes in the Cosinuss sensor orientation during the trial. Finally, the three users selected for the learning stage of the algorithm were chosen based on general characteristics (gender and age), but we did not take into account other gait related features such as body mass, leg or step length.

The promising results presented in this publication may require some more research so that the algorithm could be more independent of various gait patterns or gait styles.

The AHEAD subsystem presented in this paper is a potential candidate to be used in the ACTIVAGE project (European Large Scale Pilot on Smart Living Environments) where the main objective is to build the first European Internet of Thing (IoT) ecosystem across 9 Deployment Sites (DS) in seven European countries.

Acknowledgment

The research presented in this paper is partially funded by the European project ACTIVAGE (grant agreement 732679) and the European AHEAD project (AAL-2012-2-167), which is partially funded by the European Ambient Assisted Living Joint Programme and the National Funding Agencies from Austria, Denmark, Germany and Spain (Ministerio de Industria, Energa y Turismo). The authors would like to thank the AHEAD partners Atos, Auditdata, Austrian Institute of Technology, Bruckhoff hannover, Forschungszentrum Informatik am Karlsruher Institut fr Technologie, Innovationsmanufaktur, Johanniter, and particularly Cosinuss, the manufacturer of the ear sensor used in this experiment.

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 ISBN: 978-1-61208-565-4

TABLE I. RESULTS OF THE TRIALS PERFORMED BY HEIGHT HEALTHY SUBJECTS

Feature	Truth	Pacer	Pedometer	Walklogger	Google fit	AHEAD	AHEAD 4 best users	AHEAD 3 worst users
Walking time (s)	299 (2.2)	240 (34.6)	298.4 (5.7)	299.9 (5.6)	300 (60.0)	257.0 (39.9)	287.75 (11.9)	216 (12.5)
Number of steps	490.1 (33.8)	506.9 (46.0)	493.3 (33.5)	506.6 (45.6)	471.7 (78.7)	422.1 (51.7)	456 (35.5)	377 (28.2)
Active time	481 (2.8)	NA	NA	NA	NA	429.2 (23.6)	NA	NA
Inactive time	480.8 (1.0)	NA	NA	NA	NA	542.2 (31.8)	NA	NA

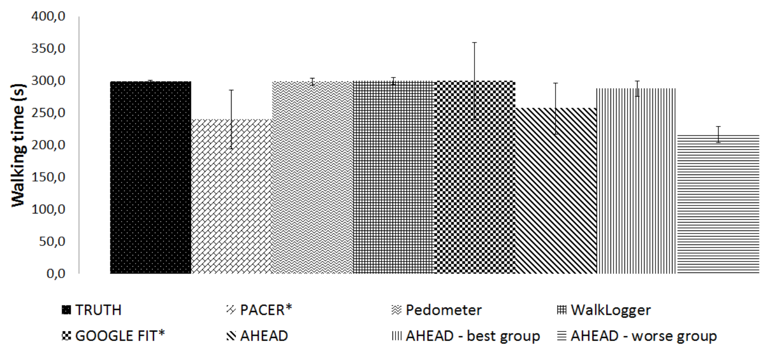

Figure 9. Testing Walking Time

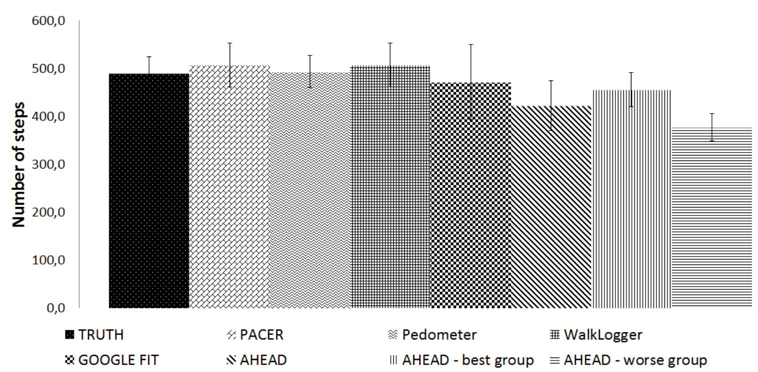

Figure 10. Testing Walking number of steps

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