Activity Level Estimator on a Commercial Mobile Phone: A Feasibility Study

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ABSTRACT
On a growing scale, we use mobile phones for diverse activities in our daily life, for example for entertainment, information or education purposes. In our present research, we assess the feasibility of using a mobile phone to unobtrusively track its user physical activity and the resulting energy expenditure; without of use of any dedicated external device. Activity Level Estimator (ALE) is an application developed for Android mobile phone which uses the built-in sensors. ALE analyzes and calculates how much time the user spends per activity level and gives estimation of his or her energy expenditure. ALE is designed to be operational as an unobtrusive, continuous real-time background application for a long-terms trend and behavioral studies in elderly care. ALE was tested with a set of users wearing the mobile phone in their pocket. Via an extensive user tests, we assessed the accuracy of ALE against a dedicated BodyMedia Sensewear device. We conclude that ALE is accurate on average 86% for different levels of walking, and it underestimates user's energy expenditure of 23% during a period of 24 hours.

Categories and Subject Descriptors
H.m [Information Systems]: Miscellaneous

General Terms
Algorithms, Measurement, Experimentation

Keywords
Energy Expenditure, Mobile Phone, Physical Activity Level, Accelerometer.

1. INTRODUCTION
Much research has been conducted to understand and reliably quantify human activity patterns, create devices and deploy services that would help and motivate its users to stay healthy and fit by increasing their physical activity in daily life, and hence to increase their energy expenditure (EE, in kcal burned). Many approaches focused on a development of dedicated activity recognition devices or algorithms, which however either require medical assistance for their reliable operation, or, are obtrusive in terms of size, weight, placement or requirement for the user's inputs. Those devices are in most cases a standalone devices composed by sensors placed directly on the user's skin [1-4], or worn on, e.g., a belt [5]. Other approaches include a use of a standalone device called pedometer, that quantifies a number of steps taken [6, 7]. There exists also an approach to have all-in-one device tracking daily activity patterns of their users by analyzing the mobile operator, i.e., GSM cell signal strength, with an algorithm based on an Artificial Neural Network [8]. The major challenge for a quantification of human activity patterns is a minimal obtrusiveness of the device chosen, as well as a maximum compliance for its wearer, especially, if the goal is to quantify users activity in ambulatory settings, i.e., in their daily life and for a long periods of time. In our research, we focus on with activity recognition in elderly care, where we aim to understand activity patterns of elderly people as well motivate them to increase the physical activity in their daily life, facilitating longer independent living.

The recent trends show that people tend to naturally carry their mobile phones (especially smart phones) with them along their daily life activities [9], hence in our research we focus on a feasibility study of an activity estimation algorithm deployed directly on a smart phone (and taking advantage of its build-in sensors); without any dedicated external devices. The *Activity Level Estimator (ALE)* is a prototype application made for an Android mobile phone, having the following requirements and design constraints. ALE estimates the activity level based on the user's movement patterns using the phone's build-in 3D accelerometer and it monitors the acceleration density during a defined time interval, assuming that the phone is worn in user's pocket, near the user's hip. The activity level is computed based on the *Metabolic Equivalent of Task (MET)* [10, 11] determined by the acceleration during a time interval and then adjusted with the *Resting Metabolic Rate (RMR)* [12] of the user. The ALE's MET was been calibrated in a multiuser test conducted in the first phase in our research. Furthermore, ALE accuracy has been evaluated along user real life activities against a dedicated, external activity monitoring device called SenseWear by BodyMedia [13]. This device is an armband device considered as a gold standard for ambulant activity estimation [14, 15]. In this paper, we present the development process of ALE and its accuracy evaluations results acquired along users test.

2. METHODS
2.1 Subjects Study Phases
ALE has been developed based on a close collaboration and feedback from a large group of its potential users. Particularly, two users studies were conducted during the design and implementation of ALE. The first user study was made to initially calibrate the ALE and it was conducted with 15 adult participants (8 female and 7 male) (*c.f.* Section 2.4). The second user study was conducted to estimate the accuracy of ALE during real life activities and conditions. This user study was composed of short-

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term study of walking activity and a long-term study of daily life activities, including driving, working on a computer and watching TV. The short-term study involved 7 users (2 female and 5 male) for the short-term study and by 1 user (male) for the long-term study (*c.f.* Section 4). For both study, we collected participant's personal information like weight, height and age. We also noted the type of the shoes and pants worn along the experiments.

2.2 Mobile Phone Instrumentation

The body acceleration was monitored by the 3D accelerometer build-in in the mobile phone (HTC Desire with Android operating system version 2.1) and with a frequency set at 40 Hz (chosen based on the dedicated controlled-lab experiments for the ALE sensitivity and for minimum phone’s battery use; the report on these results is left outside of the scope of this paper).

The mobile phone was worn in the front pocket (left or right, as chosen by the user) of the user's pants. The phone was not required to have a pre-defined fixed position. For the accelerometer readings from the phone (*x, y, z*), we have compensated the gravity factor depending on the given orientation of the phone. After the gravity compensation, we derived the *vector of acceleration* (*Va* m/s^2), i.e., independent from the given orientation of the phone. This approach was also taken in a similar research[16].

2.3 Data Processing

ALE analyzes the raw accelerometer data *Va* as follows. First, it filters the row accelerometer signal with two filters and a scale, then it calculates a *median* acceleration density during a predefined observation time interval (*DT*). Finally, it compares this result with the activity-predefined levels.

ALE filters the *Va* to remove noise and also to condensates the signal in a time interval. There ecist 2 filters cascaded one after other. The first filter keeps only high values on a sample of 16 Va data points with a moving sample window during the time interval DT. The second filter is a second pass over the data and calculates the average on a smaller sample (8 Va data points) Finally we scale all data from the time interval DT with a factor of 20%. This factor was defined during the dedicated controlled-lab experiments and it enables to increase the visibility of high *Va* values in the signal and to avoid overlapping results among defined thresholds. The time interval DT was defined by an empirical experimentation and was fixed to 2 seconds (~60 accelerometer data points). We have made this choice via heuristics, i.e., if the time interval is too short, the computed *Va* median too much vary between consecutive DT, and if it was too long, low value data points minimized the result resulting in an under-estimation of activity level. We also use DT to detect if the acceleration indicates a continuous longer activity spanning across multiple DTs, or it is just a small movement of the body within a DT. Finally, we compute the Va median of the filtered signal during the DT and we scale it to increase the difference among the acceleration density. This median represents *the level of the acceleration density*. We used median instead of an average because the average was too influenced by outliers existing in the accelerometer data; the median reflected better the user’s activity levels depending on the density of the accelerometer signal.

The Figure 1 represents the data resulting for 6 seconds of activity (three footsteps) along the data processing phases described above. We can observe from the grey thin line (raw signal) the result after filtering with the dash line (filtered signal). The grey dot line represents the time interval boundaries (DT = 2sec) and the black bold line the median level of the acceleration density computed for this period DT.

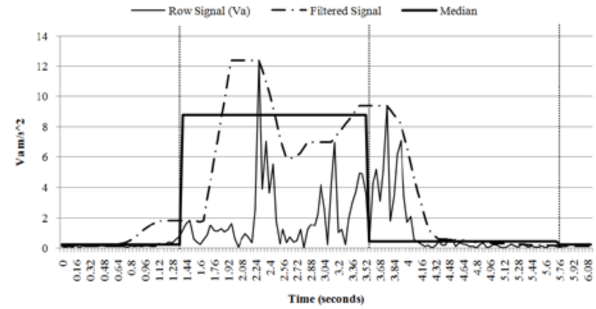

Figure 1 From the accelerometer raw signal to the median acceleration density

2.4 Thresholds calibration: First User Study

To estimate if the median level of the acceleration density (*Va*) corresponds to a given physical activity level, we defined different thresholds. Each threshold corresponds to a physical activity level predefined as follow: Sedentary, Very low, Low, Moderate and Vigorous. Sedentary level corresponds to a non-activity like standing, sitting or lying, Very Low level to a very slow walking, Low level to walking at a normal speed, Moderate level to a fast walk (or a slow run) and Vigorous level to very active physical activities like running.

Each level matches to a Metabolic Equivalent of Task values (MET) [10, 11]. The thresholds were defined by the user study, in which we asked 15 subjects to walk at different speeds with a minimum of 30 steps each, corresponding to three activity levels: Very Low (VL), Low (L) and Moderate (M). The prototype was installed on the mobile phone and worn by participants in the front left pocket of the pants. We analyzed the results with respect to user height, weight and gender variables, to determine their influence on the acceleration density. Clothes and shoes were also variables that influenced on a small scale the results, but our user study was too short for a strong analysis of these variables.

The median level of the acceleration density thresholds were actually already pre-defined during the ALE prototype implementation; our main goal for this user test was generalization, i.e, adjustment of these thresholds for many users with different physical characteristics. Thresholds values correspond to the median result of the vector of acceleration (*Va* m/s^2) in DT scaled, i.e., increased by 20% as explained earlier. For the VL level, we defined it at Va >= 1.5 and < 7, L level at Va >= 7 and < 12, and M at Va >= 12 and < 18. Figure 2 presents an example of result from one user. We can observe three activities separated by the dash line (representing the three walks). Dash lines also represent the high limit of thresholds. The bold line represents the acceleration density median computed for each DT. We observe that the three activities stay well under the limit of the corresponding thresholds. The first and the last median measured for each activity shows that it is all the time below the threshold. When the user starts to walk, he accelerates from a non-movement. Similarly, when user stops his walk, he decelerates. For that reason, in ALE we added the condition that median from a n^{th} DT was valid to be classified in some threshold only if the DT before (n-1) or after (n +1) was also classified. This condition was also made to remove false movements detected within a DT while the user is sitting or standing.

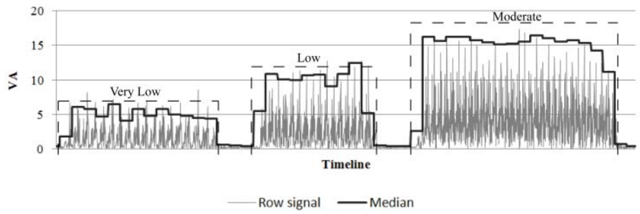

Figure 2 Example result for the first test study represented the three walks activities

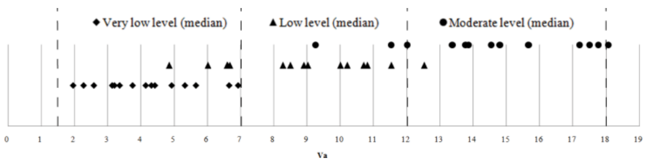

Figure 3 Results for each activity level of the first user study

The Figure 3 represents results for three activity levels of each walk. We can see that some results overlap amongst the activity levels. To explain these overlapping results, we analyzed the influence of the following variables on the results: user height, weight and gender. Regarding the height, we observed that it had an influence and tried to understood the reason for that. Most probably it is related to length of the user legs. When the mobile phone is on the pocket, it follows the rotation of the leg, so the movement can be measured by the angle made by the leg. Of course, if the user is tall, the distance - performed by the foot - from the start to the end of the step will be larger, than if a user is shorter, but angle will be quite the same. On the other side, the movement's speed will be higher for a taller user with a high distance performed by the foot. For the weight variable, the acceleration was influenced by weight as a vector of force. We found however, that the gender was the variable with the most influence. For this variable, we do not have any explanation apart from an anatomy and resulting difference in walking style.

In the Table 1, we resume users characteristics and results for walking activities. Values given on the table represent the mean activity level over all subjects for each walking session. .

Table 1 Characteristics and results of subjects

		Female (n = 8)	Male (n = 7)
	Weight, kg	63.88 ±12.12 (51-85)	82.14 ±12 (65-100)
	Height, cm	166 ±6.6 (156-175)	178 ±3.9 (172-183)
Mean Activity (*Va*)	**Very low level**	3.50 ±0.8 (2.27-4.42)	4.95 ±1.80 (1.96-6.92)
	Low level	7.23 ±1.68 (4.86-10.22)	10.51 ±1.31 (8.91-12.53)
	Moderate level	13.67 ±3.12 (9.26-18.1)	15.62 ±1.59 (13.37-17.77)

* Values represent mean, standard deviation and the range in parentheses.

From Table 1, we observe that the values are lower for female participants. The L level threshold definition was too high for them; 5 out of 8 values from women subjects for this level were lower than 7 with a range of 4.86 to 6.62 (recall that the limit was set at 7 to 12). Therefore we changed our ALE algorithm to take into account the gender variable and adapt the thresholds correspondingly. For female, we set the L level for 6 to 11. To resume, we have used the first user study to calibrate the thresholds Va for different activity levels, we have concluded that the main adaptation of our algorithm shall be done based on the gender variable.

2.5 Energy Expenditure Processing

Each activity level (VL, L, M, V) is represented by a *basal* MET value. We defined these values based on work of [10, 11] and on internal experimentations done with the SenseWear device from BodyMedia [13] (see Table 2).

Each MET is adjusted with the RMR of the user, after work of Byrne et al. [12], proving that the basal MET (1 MET) overestimates the energy expenditure by 20%. They have concluded that based on large scale user study (500+ subjects), where they have measured the RMR of each person with different methodologies, e.g., indirect calorimetry using a ventilated hood system and respiration chamber. Based on these and on controlled-lab activity monitoring experiments, they proposed to adjust the MET level with the measured RMR as follows (1).

$$MET\_adjusted = MET\ level * (1MET/\ RMR\ (kcal\text{-}kg^{-1}\text{-}h^{-1}))\ (1)$$

ALE estimates the EE in calories based on the time spend per an activity level (t), the MET (following the activity level) adapted with (1) (*MET_adjusted*), and the user weight in kilograms (w) along the equation (2). The RMR used for (1) was estimated with the Harris-Benedict equation [17].

$$EE(kcal) = MET\_adjusted * t * w\ (2)\ [18]$$

The Total Energy Expenditure (TEE) is also estimated. TEE is a prediction of calories burned in 24 hours for the current day; at midnight it estimates calories burned for the next 24h assuming resting (i.e., standing, sitting or lying) at the sedentary activity level and along the day, it adds additional calories burned corresponding to different activity levels.

Table 2 MET values per activity level

Activity level	MET
Sedentary	1
Very low (VL)	2.5
Low (L)	4.5
Moderate (M)	6
Vigorous (V)	9

3. DESIGN AND IMPLEMENTATION

ALE was developed for Android operating systems (version 2.1) and uses phone's build-in 3D accelerometer. ALE starts with the system and runs continuously in the background of the OS, even when the phone is not used and the screen is locked. A simple GUI was also created to manage the user settings and see the results in real-time. On this screen, ALE displays four color bars (one per each activity level VL, L, M and V) corresponding to the duration of activity (Figure 4) in the current day (i.e., since midnight). The scale of the displayed figures can be adjusted via a touch. We have made the choice to not display the sedentary level because the time for it is generally much higher comparing the other activity levels, and to keep the user's motivation high, we keep this information in the background. The GUI display results in kcal computed for all activity levels (except the Sedentary level) and the TEE in kcal predicted for whole 24 hours.

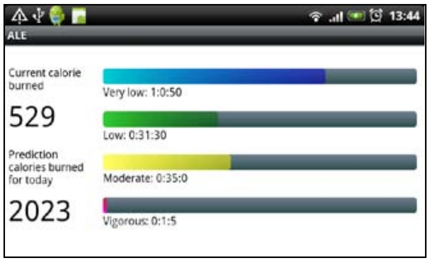

Figure 4 Screenshot of the main screen of ALE

All day results are stored on the same phone on a SQLite database and the user can see past result on his mobile phone. For our experimentation, we have also added a functionality to log all events of the application to the file.

4. ALE ACCURACY

To evaluate the ALE accuracy, we have conducted a study in two phases with seven subjects. The subjects at the same time were wearing the armband device SenseWear and the mobile phone running ALE.

SenseWear is a dedicated portable device for activity monitoring (Figure 5) and manufactured by BodyMedia [13]. The device is worn on an arm over the triceps muscle and has the capability to monitor the wearer's energy expenditure. It contains sensors like: 3D accelerometer, galvanic skin response, skin temperature and heat flux. SenseWear measures the total energy expenditure (TEE kcal), physical activities levels (MET), steps and sleep efficiency.

Figure 5 SenseWear device from BodyMedia [13]

SenseWear is considered the 'gold standard' for ambulatory assessment of energy expenditure [14, 15] and therefore we selected it as the base device to compare MET results with ALE. The first phase was conducted to determine the accuracy of MET estimation of ALE during a dedicated walking activity. The second phase was to determine its accuracy during a complete day (24h), where the subject followed his usual daily life activities.

4.1 First Phase: Walking Activities

For the first phase of the user study, we asked the subjects (n=7) to walk outdoors in an open space having a measurement session lasting minimum 15 minutes. We asked subjects to walk sometimes slowly (VL and L activity level) and sometimes quickly (M). Walks were conducted in different geographical places with different grounds. Most of these walks were on road with different elevations. SenseWear and ALE were configured based on the subject's the weight, height, gender and age. We have made note upon the subjects' clothes as well (i.e., where the phone with ALE was put), and shoes type. SenseWear was additionally configured along the subject being left or right handed. For ALE this is not an important variable, because the phone with ALE is located in the lower part of the user's body. The Table 3 resumes the characteristics of the subjects in this study.

Table 3 Characteristics of subjects in evaluation

Subjects	Female (n = 2)	Male (n = 5)
Weight, kg	62.5 ±14.8 (52-73)	70 ±9.6 (65-87)
Height, cm	165.5 ±13.4 (156-175)	180.2 ±3 (178-184)
Age, year	25.5 ±3.5 (23-28)	29.2 ±2.5 (26-31)
RMR, kcal	1439.8 ±184.5 (1309 – 1570)	1731.9 ±153.4 (1640 – 1994)

* Values represent mean, standard deviation and the range in parentheses.

SenseWear returns MET values measured during the one-minute period, while ALE during a 2-seconds period. As SenseWear was our baseline device, hence we averaged ALE's MET values for every minute. Then we computed the average MET value during the complete walk session for both devices. Finally, we analyzed in percent the difference for the whole session between the SenseWear and ALE MET results using the Mean Percent Error (MPE) (3), and the minute-by-minute difference using the Mean Absolute Percentage Error (MAPE) (4).

$$\frac{(MET^{ALE} - MET^{SenseWear})}{MET^{SenseWear}} \qquad (3)$$

$$\left|\frac{(MET^{ALE} - MET^{SenseWear})}{MET^{SenseWear}}\right| \qquad (4)$$

Moreover, we computed the proportion of overestimation and underestimation of MET by ALE comparing to SenseWear for the complete session.

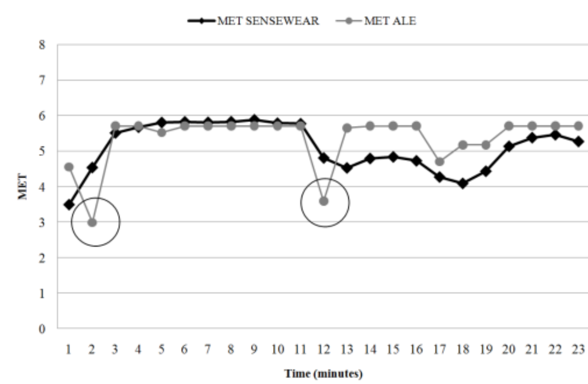

Figure 6 Example 1: MET per minute results from both devices performed by one subject

The Figure 6 shows the result of a walk performed by a male subject along 23 minutes walk on a street road. The black line represents MET estimated by the device SenseWear, The grey line, MET estimated by ALE and the corresponding MAPE values are summarized in Table 4.

Table 4 Example 1 ALE evaluation results

	Sensewear	ALE	MPE for the session
Average MET	5.12	5.35	4.47%
Overall MAPE per minute		11.98%	
Proportion of MET overestimation in a session		60.87%	
Proportion of MET underestimation in a session		39.13%	

For the given subject test example, ALE underestimates MET twice (Figure 6), at minute 2 and 12, when the subject stopped walking for less than a minute. It means that ALE was more sensitive for this case than SenseWear. This illustrates our point of difference in results granularity. During the session, we asked to the subject to reduce his speed and after about 7 minutes to walk faster. MET were estimated from thresholds and for this case, the walk activity was the edge of being classified as L/M level and ALE classified it as a M (moderate) level (*c.f.* Section 2.4). Therefore, from minute 13 we observe that ALE overestimates MET.

If we compare the MPE and MAPE per minute results from the Table 4 we conclude as follows. For this particular case of session, we found that ALE overestimates of 4.47% the total calories burned during this particular test. For the MPE, most errors were compensated by the over / underestimation trends during the whole session and did not represent the average error per minute, being 11.98%.

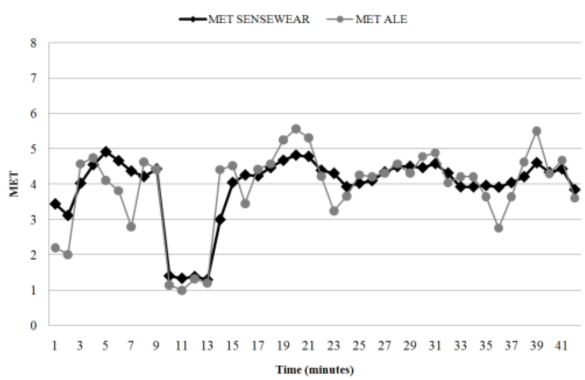

Figure 7 Example 2: MET per minute results from both devices performed by one subject

Table 5 Example 2 ALE evaluation results

	Sensewear	ALE	MPE for the session
Average MET	3.95	3.83	-6.99%
Overall MAPE per minute		12.52%	
Proportion of MET overestimation in a session		47.62%	
Proportion of MET underestimation in a session		52.38%	

The Figure 7 represents a 42 minutes Low activity level walk session in a forest with small hills where the subject took his dog for a walk. The road was not flat and had lots of holes and stones. The given environment was very interesting because such ground was never tested before and based on the results we expected to see how ALE was able to compensate disjointed body movements. At different moments along the session, the subject stopped walking because of the dog. These stops resulted in errors and increased the ALE underestimation proportion as given in the Table 5. Finally, we found an underestimation of 6.99% for the MET average values.

The Table 6 represents all results for the first evaluation phase of ALE along the walking sessions for 7 subjects. With the average MAPE per minute, we conclude that ALE is accurate at 86% for walking activities. It is not possible to clearly determine if ALE has more tendency to over- or under-estimate user's activity level, because the trends indicate tendency for both, and particular trend is user dependent.

4.2 Second Phase: Real World Evaluation

Because our goal is to use ALE in real world environments, along the user's daily life activities and along long periods of time for the user's behavioral studies, we conducted a long-term ALE evaluation along an arbitrary three days from user's life, accumulating in total about 30 hours of continuous user's activity data. There were 3 separate sessions lasting 6 hours, 15 hours and 9 hours. We instructed the subject to follow normal daily life activities and to disconnect both devices when sleeping. Characteristics of the subjects are: male, 65 kg; 178 cm; 31 years old; RMR 1640 kcal/day.

We present example results of this test below (Figure 8, Figure 9 . The figures present MET values per minute for both devices. We have added annotations into figures that represented some activities of the user, like driving, shopping and working (the labels were provided by the user at the end of each day).

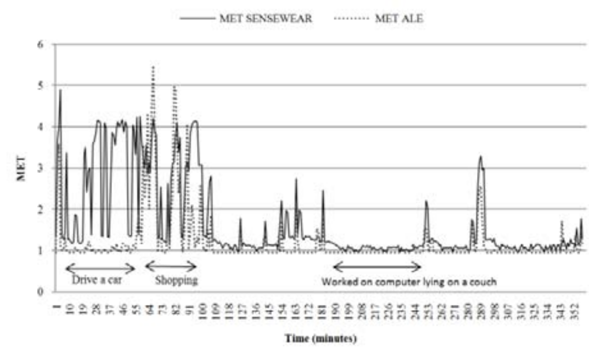

Figure 8 MET per minute results from both devices (6 hours)

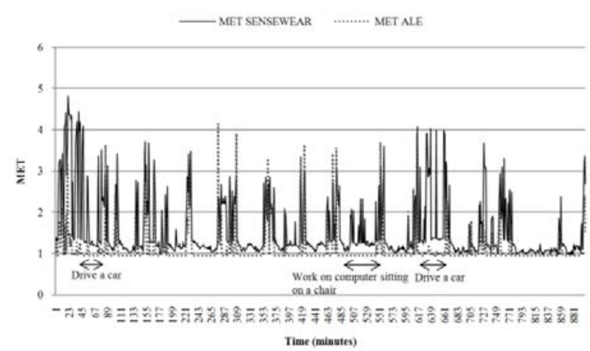

Figure 9 MET per minute results from both devices (15 hours)

In the Table 6, we also include the evaluation results for the second phase. We observe that ALE has an MAPE per minute higher for the second phase than for the first one and it tends to underestimate MET by 27.9%, 95.05% of the time. That means that ALE was not able to detect all kind of activities like SenseWear did. In Figure 8 and Figure 9, we represented different subject's daily life activities. For example, in Figure 8, we note driving, which SenseWear classified as activity with a MET from 1.2 to 4, and ALE with MET from 1 to 1.2. ALE was not designed to detect this kind of sedentary physical activities. Again, on the Figure 8, we observed a long period when the subject was lying on a couch and worked on computer, which was not properly classified by ALE. Other example on the Figure 9, we noted a part

Table 6 Evaluation Results for the two evaluation phases

I	Period	SenseWear MET Average	MET ALE Average	MPE (%) for session	MAPE (%) per minute	Proportion (%) of overestimation for session	Proportion (%) of underestimation for session
1	22'	5.12	5.35	4.47	11.98	60.87	39.13
2	23'	5.12	4.77	6.77	8.98	13.64	86.36
3	15'	4.12	3.96	3.85	14.02	53.33	46.67
4	25'	4.26	4.72	10.75	19.27	75	25
5	25'	3.99	4.54	13.7	17.27	83.33	16.67
6	42'	3.95	3.83	3.01	12.52	47.62	52.38
7	44'	4.28	4.4	2.86	15.97	65.12	34.88
	Average	**4.4**	**4.51**	**6.49**	**14.29**	**56.99**	**43.01**
II							
1	6h00	1.69	1.19	-29.78	23.18	5.87	94.13
2	15h00	1.56	1.13	-27.54	23.68	3.88	96.12
3	9h40	1.53	1.13	-26.37	23.36	5.11	94.89
	Average	**1.6**	**1.15**	**-27.9**	**23.41**	**4.95**	**95.05**

of the day when the subject worked on a chair. We think that SenseWear is able to quantify energy expenditure for these physical as well as cognitive activities because of its additional sensors like skin temperature and galvanic skin response. ALE was not able to detect that because, except arm, the subject did not move. However, as we see in Figure 8, the shopping activity was detected by ALE almost as accurately (average MET 1) as by SenseWear (1.2 MET).

5. DISCUSSION AND CONCLUSION

We developed an activity level estimator deployed on a commercially available mobile phone, this ensuring its minimal obtrusiveness (i.e., it is a background application) and maximum compliance (i.e., as research shows that we tend to carry our phone anywhere with us). We evaluated ALE against SenseWear from BodyMedia, a gold standard for energy expenditure estimation.

Our results showed an overall average error of 14.29% (hence accuracy of 85.71%) per minute (and 6.49% per a session) for walking only activities, and average error of 23.41% per minute (and 27.9% per a session) during different daily life activities, like driving, shopping, working or just relaxing. The SenseWear device detected energy expenditure for cognitive sedentary activities, for example working while sitting on a chair. ALE was designed to detect and quantify body movements and was not able to detect this kind of sedentary activities. The fact that ALE underestimates the energy expenditure of the user can be seen positively, assuming that by this means, it can prevent the user from overestimating his energy intake needs and from overeating.

Finally, we conclude that overall evaluation results for ALE are very encouraging and we proved that it is feasible to develop an accurate activity level monitoring, quantifying user body movements on a commercial mobile phone. The SenseWear device uses other build-in sensors, like galvanic skin response and temperature to achieve its highest accuracy, but these sensors are (not yet) available in a mobile phone.

We are preparing more experiments and more user tests, which results will enable us to improve our application. For example at first, we plan to conduct a user study with the use of a treadmill with more subjects walking the same distances at the same speed. Moreover, we plan to conduct more user studies along their daily life activities, and we are especially looking forward to apply our solution for elderly care purpose.

6. REFERENCES

[1] Barralon, P., et al. *Walk detection with a kinematic sensor: Frequency and wavelet comparison*. in *Proceedings of the 28th IEEE EMBS Annual International Conference*. 2006. New York City, USA.

[2] Foerster, F. and Fahrenberg, J. Motion pattern and posture: correctly assessed by calibrated accelerometers. *Behavior Research Methods Instruments and Computers*, 32, 3, (2000), 450-457.

[3] Mathie, M. J., et al. Classification of basic daily movements using a triaxial accelerometer. *Medical and Biological Engineering and Computing*, 42, 5, (2004), 679-687.

[4] Wang, N., et al. *Accelerometry based classification of walking patterns using time-frequency analysis*. in *Proceedings of the 29th Annual International Conference of the IEEE EMBS*. 2007. Cité Internationale, Lyon, France.

[5] Akay, M., et al. Unconstrained monitoring of body motion during walking. *IEEE Engineering in Medicine and Biology Magazine*, 22, 3, (2003), 104-109.

[6] Connelly, K. H., et al. Mobile applications that empower people to monitor their personal health. *e & i Elektrotechnik und Informationstechnik*, 123, 4, (2006), 124.

[7] Sunny, C., et al. Design requirements for technologies that encourage physical activity. In *Proceedings of the SIGCHI conference on Human Factors in computing systems* (Montreal, Quebec, Canada, 2006). ACM.

[8] Anderson, I., et al. Shakra: Tracking and Sharing Daily Activity Levels with Unaugmented Mobile Phones. *Mobile Networks and Applications*, 12, 2, (2007), 185.

[9] Patel, S., et al. Farther than you may think: An empirical investigation of the proximity of users to their mobile phones. *UbiComp 2006: Ubiquitous Computing*(2006), 123-140.

[10] Ainsworth, B. E. *The Compendium of Physical Activities Tracking Guide*. Prevention Research Center, Norman J. Arnold School of Public Health, 2002. Retrieved 27.09.2010, from http://prevention.sph.sc.edu/tools/compendium.htm.

[11] Ainsworth, B. E., et al. Compendium of physical activities: an update of activity codes and MET intensities. *Medicine & Science in Sports & Exercise*, 32, 9, (2000), S498.

[12] Byrne, N. M., et al. Metabolic equivalent: one size does not fit all. *Journal of Applied Physiology*, 99, 3, (2005), 1112.

[13] BodyMedia Inc *SenseWear*. BodyMedia, 2010. Retrieved 08.11.2010, from http://sensewear.bodymedia.com/.

[14] Jakicic, J., et al. Evaluation of the SenseWear Pro Armband (TM) to Assess Energy Expenditure during Exercise. *Medicine & Science in Sports & Exercise*, 36, 5, (2004), 897.

[15] St-Onge, M., et al. Evaluation of a portable device to measure daily energy expenditure in free-living adults. *American Journal of Clinical Nutrition*, 85, 3, (2007), 742.

[16] Ahola, T. Pedometer for Running Activity Using Accelerometer Sensors on the Wrist. *Medical Equipment Insights*, 2010, 3, (2010).

[17] Harris, J. and Benedict, F. A biometric study of human basal metabolism. *Proceedings of the National Academy of Sciences of the United States of America*, 4, 12, (1918), 370.

[18] Ainsworth, B., et al. Compendium of physical activities: classification of energy costs of human physical activities. *Medicine & Science in Sports & Exercise*, 25, 1, (1993), 71.