Physical activity monitoring based on accelerometry: validation and comparison with video observation

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Abstract—*The objective of this feasibility study is to evaluate the use of the 'Physilog' device, an ambulatory physical-activity recorder based on acceleration measurement, for the monitoring of daily physical activities. Accelerations measured at the level of the chest and the thigh are recorded by Physilog over a period of 1 h in five normal subjects. A specially designed studio-like room allowing the performance of most usual activities of everyday life is used. A video film synchronised with the Physilog is obtained for each subject to check the accuracy of the data derived from Physilog. Based on the analysis of the average and the deviation of the acceleration signal, an algorithm is developed to classify the activities in four categories, i.e. lying, sitting, standing and locomotion. Compared with the video observations, the results from the algorithm show an overall misclassification of 10.7%, which is mainly due to confusion between dynamic activities and the standing posture. In contrast, the misclassification between postures is negligible. It is concluded that Physilog can be used in the clinical setting for the reliable measurement and long-term recording of most usual physical activities.*

Keywords—*Physical activity, Accelerometer, Ambulatory system*

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1 Introduction

DAILY PHYSICAL activity (or the restriction of it) is a determining factor of the quality of life. To date, this variable has only rarely been evaluated objectively, and in most cases its assessment has been unsatisfactory or imprecise. Self-assessment of physical activity based on questionnaires is subjective, and the discrepancy between patients' and physicians' evaluations is significant (LIEBERMAN *et al.*, 1996). However, a reliable measurement of the physical activity in everyday life would allow a better assessment of the utility and the relevance of a number of medical treatments.

In previous studies, the measurement of ambulatory physical activity often relied on the use of a single accelerometer strapped on the waist, the wrist or the ankle (PATTERSON *et al.*, 1993; SIEMINSKI *et al.*, 1997; NG and KENT-BRAUN, 1997) although heart rate monitors have also been used (HASKELL *et al.*, 1993). The problem with these methods is that they provide no information on the type of activity. Recently, new systems have been developed to identify the type of activity, but these methods need to be evaluated further in the domestic environment (MAKIKAWA and IIZUMI, 1995; VELTINK *et al.*, 1996).

Using neural network-processing of the acceleration signal, we have developed a new system for the measurement of movements, called Physilog (AMINIAN *et al.*, 1995*a*, *b*). This light, portable system is equipped with miniature accelerometers that can be attached to various parts of the body. The system allows the measurement of the incline, speed and distance covered by healthy subjects or patients with various disorders, such as, for instance, peripheral vascular disease.

The objective of this paper is to evaluate the accuracy of the Physilog system in discriminating between several static postures and dynamic activities, to allow reliable long-term monitoring of activities such as lying, sitting, standing and locomotion.

2 Method

2.1 *Body movement recording and classification*

The recordings took place in a studio-like room (5 m × 5 m) specifically designed for this purpose. The furniture and the equipment in the room included a bed, chairs, a table, a TV, a treadmill, a step-ladder, journals, books and food, so that the subject could easily reproduce most basic activities of daily life.

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Two miniature accelerometers* were strapped on the chest and on the rear of the thigh to measure the chest acceleration a_c in the vertical direction (parallel to the gravitational direction) and the thigh acceleration a_t in the forward direction (orthogonal to the gravitational direction) (Fig. 1). The chest accelerometer was attached with a belt, and the thigh accelerometer was strapped on the skin using medical tape. Both sensors were placed in the standing position.

Both signals were amplified, calibrated, digitised at 10 Hz by the Physilog† and stored on a 2 Mbytes SRAM memory card. To achieve prolonged monitoring of the physical activity, it is essential to choose a low sampling frequency. A 10 Hz sampling frequency was the best compromise, allowing both the detection of changes in posture and a long recording time (around 14 h with a 2 Mbytes memory size).

Five subjects (four males and one female) were studied. Each subject spent 1 h in the studio-like room, where he or she was free to act. To collect meaningful data, the subjects were asked to perform each type of activity (lying, sitting, standing and treadmill walking) for at least several minutes.

The acceleration signals are a function of both gravitational- and movement-related accelerations of the part of the body that carries the sensor. The 'static activities' (postures) were determined from the orientation of defined segments of the body in relation to the direction of gravitational acceleration. The 'dynamic activities' were quantified by analysis of the acceleration signals resulting from body movements during locomotion (Fig. 1). Owing to the relatively low sampling frequency, only a short frequency range of acceleration (0–0.5 Hz) was used for processing.

The physical-activity detection algorithm is shown schematically in Fig. 2. The calibrated acceleration (with its gravitational component) was lowpass filtered (0–0.5 Hz). The median values (MED) and the mean absolute deviation (MAD) of the filtered acceleration a_{cf} and a_{tf}, recorded from the chest and thigh, respectively, were computed every second. The MAD function corresponds to the average of the absolute difference between a set of acceleration data and the mean of the samples of this set. This led to the following parameters:

$$a_{cmed} = MED(a_{cf}) \tag{1}$$

$$a_{tmed} = MED(a_{tf}) \tag{2}$$

$$a_{mad} = MAD(a_{cf} + MAD(a_{tf}) \tag{3}$$

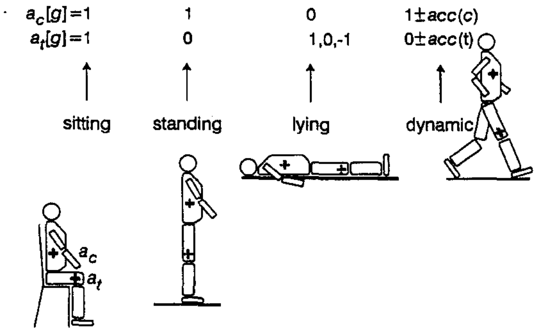

Fig. 1 *Relative values of chest a_c and thigh a_t acceleration during main activities. acc(c) and acc(t) represent chest and thigh acceleration variation during body movement*

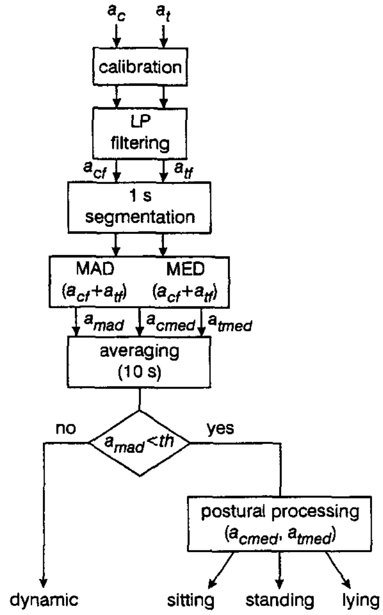

Fig. 2 *Algorithm for physical-activity detection*

These functions are an estimate of the mean (MED) and the amplitude deviation (MAD) of accelerations and are less sensitive to outliers than mean and standard deviation.

For each period $\Delta t = 10$ s, the median values of a_{cmed}, a_{tmed} and a_{mad} were computed. Although a shorter Δt increases the discrimination sensitivity for dynamic activites, it is associated with increased errors related to artefact movement, such as the transition between posture or segmental body movement while standing. In addition, because of the low frequency range of analysis (0–0.5 Hz), the value of Δt must be expanded to a few seconds. A Δt value of 10 s is chosen in this case. This leads to 360 samples for each parameter, corresponding to a recording of 1 h.

Five classes of activities were defined: lying, sitting, standing, dynamic and 'others', which includes all activities not identified as belonging to one of the first four classes. Discrimination between static and dynamic activities was accomplished by applying a threshold *th* to a_{mad}. Lying, standing and sitting postures were identified by the analysis of a_{cmed} and a_{tmed} values.

2.2 *Video recording and classification*

Each subject was filmed on a video that was synchronised with the Physilog device at the beginning of the recording. To compare the video with the acceleration recordings, the film of each subject was divided into 360 sequences of Δt. For each sequence, the activity viewed on the video was attributed to one of the five classes by observers.

There is no gold standard for the monitoring of physical activity. Even the use of video images does not prevent subjectivity in the assessment of the observations. For example, brief lower-limb movement while standing could be classified as a dynamic activity as well as static standing. To improve the objectivity of the visual assessment and a reliable classification of each performance, the following criteria were adopted:

- Walking and running were considered a dynamic activity if the subject accomplished more than two steps. If not, the performance was classified as standing.
- For each posture, voluntary movements not involving locomotion, but of a cumulative duration of more than $\Delta t/2$, were considered as dynamic.

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- A single movement associated with the transition between postures (i.e. standing to sitting) was not considered as dynamic.
- A series of movements associated with two or more consecutive transitions between postures (i.e. lying to sitting to lying) were considered as dynamic.

2.3 *Evaluation of the classification*

For each Δt, the video and Physilog classifications were compared, and the following features were defined:

- duration of each activity according either to Physilog (T_p) or to video (T_v)
- predicted error of Physilog for each activity

$$E_p = \frac{T_p - T_v}{T_v} \quad (4)$$

- sensitivity of Physilog for each activity, defined as

$$S = \frac{\text{total time that video and Physilog agree about activity 'A' at the same time}}{\text{total time that activity 'A' occurred according to video}} \quad (5)$$

- misclassification error for each subject

$$e_m = \frac{\text{total time that video and Physilog disagree at the same time}}{\text{total time of recording (1 h)}} \quad (6)$$

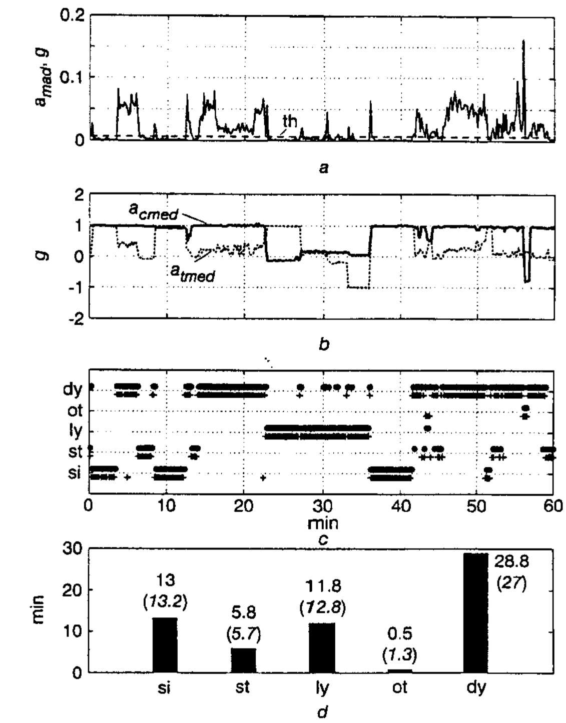

Fig. 3 *Physical activity identification during 60 min for a subject. (a) Values of a_{mad} compared with threshold th. Values above th were considered dynamic. (b) a_{cmed} and a_{tmed} values. (c) Physilog (●) against video (+) classification of activity in five classes: dynamic (dy), sitting (si), standing (st), lying (ly) and others (ot). (d) Histogram of activities obtained from Physilog, with video values in parentheses*

3 Results

The algorithm shown in Fig. 2 was used for each subject. Fig. 3 illustrates the results obtained from a single subject. Figs. 3*a* and *b* show how the static and dynamic activities were separated using an appropriate threshold *th*. Fig. 3*c* compares the categorisation of activity resulting from Physilog with what was seen on the video. Disagreement occurred mostly with transition movements (i.e. from sitting to standing), when visual observation (video) becomes less objective.

The histogram of activities corresponding to the values of T_p and T_v, is presented in Fig. 3*d*. The values of T_p and T_v for all subjects are reported in Table 1.

Table 2 shows the E_p, S and e_m values for each subject. The comparison of E_p values shown in Table 2 indicates that sitting and lying were underestimated, whereas dynamic activity was overestimated. This can be explained by the fact that a short but strong movement (lasting for less than $\Delta t/2$) occurring during sitting or lying could be interpreted as dynamic by Physilog, whereas the video observer would classify it as static.

The sensitivity S of Physilog decreases during standing. This is probably related to an incorrect classification of this posture when it is associated with transit movements that accompany posture changes (i.e. lying or siting to standing), resulting in the registration of a dynamic instead of a static event. This discrimination error could also explain the increase in E_p for subject 2, who was very active during standing.

Table 2 also shows that the misclassification error is mainly due to the confusion between dynamic activities and static standing, whereas the misclassification between postures is negligible.

To evaluate the system in a real environment, three patients were tested during their hospital stay. They carried the Physilog device for 12 h (8 a.m.–8 p.m.). Each patient used a diary to report his personal assessment of time spent in various postures, including locomotion. The results show a significant discrepancy between the Physilog recording and patient self-assessment (Fig. 4).

4 Discussion

Our study suggests that recognition of most usual daily physical activities can be achieved reliably using the portable Physilog device. The system was validated in a studio-like

Table 1 Time duration of each activity: Physilog T_p against video recording T_v

	Sitting, min		*Standing, min*		*Lying, min*		*Dynamic, min*		*Others, min*	
Subjects	T_p	T_v	T_p	T_v	T_p	T_v	T_p	T_v	T_p	T_v
1	13.0	13.2	5.8	5.7	11.8	12.8	28.8	27.0	0.5	1.3
2	16.0	18.0	6.7	5.7	9.2	9.3	28.2	25.3	0.0	1.7
3	20.3	20.7	5.0	4.7	11.3	12.2	23.3	22.5	0.0	0.0
4	29.0	30.3	2.5	2.3	4.7	4.8	23.8	22.5	0.0	0.0
5	18.7	19.3	12.2	13.2	7.3	7.8	21.8	19.3	0.0	0.3

Table 2 Prediction error E_p and sensitivity S of Physilog for each subject and each activity. e_m represents misclassification error

	Sitting, %		*Standing, %*		*Lying, %*		*Dynamic, %*		e_m, %
Subject	E_p	*S*	E_p	*S*	E_p	*S*	E_p	*S*	
1	−1.5	95	+1.8	74	−7.8	88	+6.7	91	11.4
2	−11.1	87	+17.6	65	−1.1	95	+11.5	92	14.2
3	−1.9	96	+6.4	64	−7.4	93	+3.6	89	9.7
4	−4.3	94	+8.7	64	−2.1	93	+5.8	93	7.5
5	−3.1	95	−7.6	81	−6.4	89	+13.0	90	11.1
Overall	−4.4	93	+5.4	73	−5.0	91	+8.1	91	**10.7**

room equipped with a video recorder. Each film was synchronised with the recording of the Physilog and carefully viewed by several observers who classified the physical activity of each subject in four categories (lying, sitting, standing and locomotion).

Physilog was also tested in a hospital environment, and discrepancy with self-reported patient activity was clearly established. The inaccuracy of the patient self-assessment is probably due to subjective bias. Over-, as well as under-estimation of the time spent in various activities is unpredictable and can be related to the context or to patient's expectations. Nevertheless, further clinical investigation involving a larger number of patients is needed better to understand the differences between Physilog and self-assessed physical activity.

The measuring system only needs two miniature sensors that can be placed easily on the subject without causing significant discomfort, even if worn for a prolonged period of time. However, several parameters, i.e. threshold *th*, angular threshold, sampling frequency *fs* and observation period Δt, need to be carefully selected to obtain reliable results. Furthermore, the magnitude threshold *th* used to recognise dynamic activity and the angular threshold used to discriminate between postures need to be adapted to each patient.

To provide long-term recordings, we have chosen a low sampling frequency (10 Hz), whereas other studies used 16–100 Hz (MAKIKAWA *et al.*, 1995; AMINIAN *et al.*, 1995*a*; *b*; VELTINK *et al.*, 1996). Therefore, to avoid distortion in the high frequency components of motion, processing of a narrow frequency range (0–0.5 Hz) was applied. This problem can be avoided by increasing the sampling rate, although a larger memory is required.

The effect of decreasing the duration of the observation period Δt, over which a_{mad} is averaged, is shown in Fig. 5, where a resting period, followed by a normal and a slow walking period occurs. As can be seen, the selection of the threshold *th* becomes difficult for a short Δt, and therefore misclassification between dynamic activity and rest increases. Assessing physical activity with 10 s resolution is sufficient for the majority of clinical observations. However, this period can be reduced, provided the sampling frequency is increased.

Reducing the number of sensors (i.e. only one accelerometer on the trunk) increases the misclassification error (MAKIKAWA *et al.*, 1995). Two sensor sites appear to provide optimum results and allow standing, sitting, lying and locomotion to be recognised with an overall misclassification error of 10.7%, which is acceptable for most clinical applications.

In certain cases, however, more accurate and detailed performance recognition may be needed, i.e. walking pattern (uphill or downhill), sitting positions (on a chair or in a bed), bowing, biking and running. The discrimination can be improved by using more sensors and upgrading the signal processing. The use of numerous sensors may be uncomfortable for the subject and could interfere with normal or spontaneous physical activity. Therefore it is essential to seek new techniques of acceleration signal processing to determine the most significant parameters for each specified activity.

In conclusion, the Physilog device provides the capability to record a series of posture features as well as dynamic activities. In addition, we have previously reported the measurement of step time, speed and distance using the same device. Physilog emerges as a promising tool for the long-term monitoring of mobility in various clinical applications, including chronic pain, spasticity, cardiovascular and Parkinson's disease.

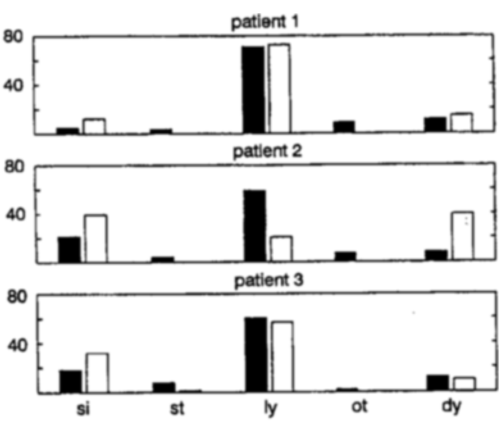

Fig. 4 *Comparison between (□) self-report evaluation of three patients and (■) Physilog estimation. Activity rate is scaled as percentage of 12 h of recording*

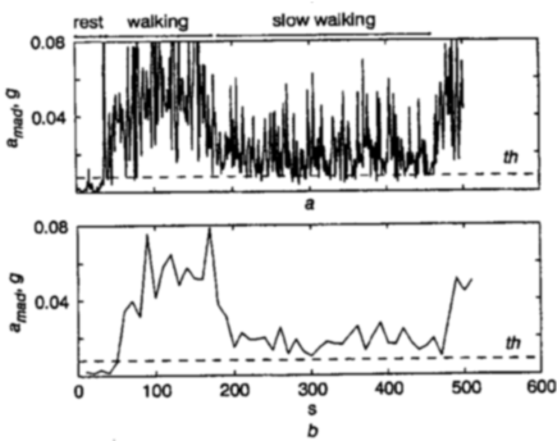

Fig. 5 *Values of a_{mad} obtained for (a) $\Delta t = 1$ s and (b) $\Delta t = 10$ s. Better distinction between 'static' and 'dynamic' activity is obtained with $\Delta t = 10$ s*

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Author's biography

KAMIAR AMINIAN was born in Tehran, Iran, in 1958. He received his Electrical engineering degree in 1982 and a PhD degree in the field of Biomedical Engineering in 1989 from the Swiss Federal Institute of Technology in Lausanne (Switzerland). Since 1982 he worked in the Metrology Laboratory of the Swiss Federal Institute of Technology in Lausanne. From 1994 to 1996 he was Assistant Professor at the Sharif University of Technology in Tehran. In 1996 he again joined the Metrology Laboratory of the Swiss Federal Institute of Technology where he is responsible for the medical instrumentation group. His research interests include transducers, human body movements analysis, ambulatory systems for measurement of physiological information and biomedical signal processing.