# Motion pattern and posture:

# Correctly assessed by calibrated accelerometers

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Revised March 2000

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This research was supported by the Deutsche Forschungsgemeinschaft Fa 54/14

We thank Manfred Smeja, Ulli Ebner, and Tanja Thielgen, postgraduate and graduate students, for their assistance in data acquisition, and Marcus Cheetham for improving the English version of this article.

Abstract

Basic motion patterns and posture can be distinguished by multi-channel accelerometry, as recently shown. A refinement of this methodology appeared to be desirable to further increase its validity, especially to distinguish walking and climbing stairs, and body rotation during sleep.

Recordings were made of 31 subjects, according to a standard protocol comprising thirteen motions and postures. This recording was repeated three times with appropriate permutation. Five uni-axial sensors and three sites of placement (sternum with three axes, right and left thigh) were selected. A hierarchical classification strategy used a standard protocol (that is, individual reference patterns) to distinguish subtypes of moving behaviors and posture.

The analysis method of the accelerometer signals yielded a reliable detection of 13 different postural and activity conditions (only 3.2 % misclassifications). A minimum set of sensors can be found for a given application, for example, a two-sensor configuration would clearly suffice to differentiate between four basic classes (sitting, standing, lying, moving) in ambulatory monitoring.

Keywords: Ambulatory monitoring, Accelerometer, Movement, Physical activity, Posture.

# Motion pattern and posture: Correctly assessed by calibrated accelerometers

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The assessment of movement and posture, and, generally, the kinematic analysis of behavior has greatly profited from the progress made in sensor technology and advanced methods in signal analysis. The conventional methodology made use of wrist-worn actometers, tilt-switch transducers, mechanical pedometer, piezo-ceramic sensors, and other electronic devices to register movements. Actometer devices are suitable for many applications. Actometer are less expensive than the infrared-light methodology of kinematic analysis, easier to apply than recordings of the electromyogram, and more convenient than video tape analysis. The measurement of activity in psychology and medicine was reviewed by Tryon (1991; see, also, Bussmann, 1998).

The progress in the assessment of movement and posture resulted from three developments: the wide bandwidth of new piezoresistive (for example, ICSensor Model 3031, Analog Devices ADXL202) and piezocapacitive sensors paved the way for the development of a new methodology with calibrated accelerometers. The DC signal output (that is, signal output < 0.5 Hz) allows the assessment of change in position in relation to the gravitational axis (that is, inclination in degrees); the AC signal output > 0.5 Hz, in terms of the gravitation, that is, g (or milli-g), represents acceleration along the sensitive axis of the device. Secondly, the development of pocket-sized digital data recorders has especially facilitated the multi-channel ambulatory monitoring and the 24-hour recording of activity in daily life. Thirdly, the increase in computer capacity that made advanced methods of signal analysis possible, for example, joint time (amplitude) – frequency analysis and specific methods of filtering (e.g., Quian, & Chen, 1996), benefited behavior analysis, too. Software has been developed for automatic detection of motion patterns in multi-channel recordings.

Multi-channel accelerometry with calibrated sensors is thus a very promising methodology, and researchers have become increasingly aware of the many advantages of this approach and of its potential fields of application in psychology and medicine (see Bussmann, 1998; Jain, Martens, Mutz, Weiß, & Stephan, 1996; Veltink, & van Lummel, 1994). The actual posture and the pattern of motion (beyond the measurement of physical activity) basically provide a frame of reference for the evaluation of many behaviors, symptoms and physiological changes. For example, the assessment of resting condition vs. walking or climbing stairs appears to be an essential aspect in the psychophysiological investigation of cardiovascular change and energy expenditure under naturalistic conditions (Tuomisto, Johnston, &Schmidt, 1996). Furthermore, the detection of body rotation (whether the subject is sleeping on the left or right side) may be important for a more precise evaluation of nightly blood pressure changes since the blood pressure measurement refers to the level of the heart. Unnoticed body rotation may thus introduce arbitrary changes in the order up to 20 mm Hg.

Further examples for the use of this methodology would be the assessment of gait, of stability of posture, of movement disorders (see Bussmann, 1998; Veltink, & van Lummel, 1994) and movement pathologies, for example, the quantification of amplitude, frequency, and occurrence time of tremor in Parkinson's disease and its relationship with posture and motion (Foerster, & Smeja, 1999; Smeja et al., 1999; van Someren et al., 1998).

<u>Multi-channel accelerometry</u>

Multi-channel (multi-site) accelerometry was evaluated recently in a number of ambulatory monitoring studies. The evaluation indicated the importance of the following issues: Which algorithms are suitable for the <u>detection of motion patterns and posture</u>, and which <u>sensor placements</u> would provide a minimal configuration to assess a broad spectrum of functional activities? (Busser, 1994; Busser, Ott, van Lummel, Uiterwaal, & Blank, 1997; Bussmann, 1998; Bussmann, Tulen, van Herel, & Stam, 1998; Bussmann, Veltink, Martens, & Stam, 1994; Fahrenberg, Foerster, Müller, & Smeja, 1997; Fahrenberg, Müller, Foerster, & Smeja, 1996;

Foerster, Smeja, & Fahrenberg, 1999; Kiani, Snijders, & Gelsema, 1997; van den Weijer, Smits, de Haan, & van Lummel, 1994). Which sensor placement is to be preferred for the prediction of overall physical activity and energy expenditure? (Bouten, Verboektet-van de Venne, Westerterp, Verduin, & Janssen, 1996; Middelkoop van Dam, Smilde-van den Doel, & van Dijk, 1997; Myrtek, Brügner, & Müller, 1996; Patterson, Krantz, Montgomery, Deuster, Hedges, & Nebel, 1993; Richardson, Leon, Jacobs, Ainsworth, & Serfas, 1995; Tuomisto, Johnston, & Schmidt, 1996; Walker, Heslop, Plummer, Essex, & Chandler, 1997).

With a few exceptions, the aforementioned studies refer only to a small number of motion patterns. It is obvious that in addition to standing, sitting, lying, walking, climbing stairs, further behaviors should be included (Bussmann et al., 1998; Foerster et al., 1999). Subtypes of lying, that is, lying on the right or left side, supine or with back supported, and a preferred position at sleep onset, are necessary to monitor bed rest and nightly body rotation. Samples of walking at normal and fast pace are desirable to test the discrimination between walking and the climbing of stairs. The majority of investigations have only used a few sensors. In some instances, it appears doubtful, whether such sensors were calibrated. Several studies did not explicitly refer to the DC-component as an indication of posture (inclination) and seemed to be content with just the analysis of movement. In addition, the subject samples studied were always small. However, posture and motion patterns exhibit a remarkable interindividual variability. To investigate such effects, a larger number of subjects is required.

The algorithm for the detection of posture and motion patterns is still a crucial aspect of accelerometry. Several suggestions have been made as to how to achieve an adequate data reduction and to differentiate between a variety of dynamic activities under investigation. The development of pattern recognition systems based on different strategies was proposed. Such classifier systems could be designed by using statistical algorithms, conventional or fuzzy logic, or artificial neural networks (Kiani et al., 1997; Martens, 1994). However, only two approaches have been used to a greater extent (Bussmann et al., 1998; Fahrenberg et al., 1997; Foerster et al., 1999).

<u>Fixed-threshold classification.</u> Motion patterns, for example, walking, climbing stairs, and cycling are discriminated by applying a threshold to the signal of the thigh accelerometer. The threshold is derived from empirical studies and is used for all subjects. The discrimination between more classes of motion patterns requires an increasing number of threshold values and appropriate normative studies. Substantial interindividual differences in static and dynamic behaviors will clearly lead to misclassifications.

<u>Reference-pattern based classification</u>. The detection of motion patterns can be improved if individual reference patterns for each postural and activity condition were obtained by an initial recording of the essential patterns under investigation. Relating to such a standard protocol, multivariate analyses and pattern similarity coefficients can be used for the detection and labeling of an actual segment, that is, motion pattern with reference to the standard protocol (Fahrenberg et al., 1997; Foerster et al., 1999).

From this (these considerations?) we suggest the use of a reference-pattern based classification rather than a fixed threshold classification whenever possible. The standard protocol takes less than a minute of recording for every posture and motion. The protocol can be easily adapted to specific subsets of behaviors and the strategy is highly flexible since certain reference patterns may be included later, if necessary, after the conclusion of the monitoring. Further refinement of the reference pattern based classification might be achieved by a hierarchical strategy which classifies postures and, subsequently, uses reference patterns for the discrimination between subsets of dynamic activities.

Only two studies have actually evaluated the discriminatory efficiency of different sensor configurations empirically based on subject samples (Bussmann, 1998; Fahrenberg et al., 1997; see also Veltink, Bussmann, de Vries, Martens, & van Lummel, 1996). The selection of a minimal configuration would be of practical interest.

The main objectives of the present study are the following:The new investigation should evaluate the hierarchical classification of patterns. This refined methodology should reduce the percentage of misclassifications reported previously, especially with regard to the difficult discrimination between walking and climbing stairs (Foerster et al., 1999).

An extended standard protocol should contain static and dynamic behaviors which were not accounted for previously, subsets of sitting posture (learning forward and backward), and particularly lying (body rotation and a lying position, back supported and knees slightly bent). The measurement of body rotation required an additional sensor placed onto the sternum, sensitive in y-direction (lateral). A sensor for the z-direction (vertical) indicates lying independent of body rotation and should be useful to distinguish between climbing stairs and walking. Lying prone was not included because the placement of the recording system and sensors were not suited for this condition (to inconvenient ??). Basically, there is no problem to detect this position if desirable (necessary/thought to be important).

The increase in the number of sensors and axial representations of movements does, however, raise the question concerning the choice of a sensor configuration which suffices to correctly detect the major classes of posture and motion. The answer will depend partly on the selection of movements and functional activities. However, the main classes of posture and a set of basic motion patterns may be seen as the core pattern. Which sensor placement gives the minimal configuration for detection of these core patterns? It can be expected that a sensor configuration may evolve which can be recommended for ambulatory monitoring of such basic classes of posture and motion patterns. An extended configuration using a larger number of sensors may account for the detection of essential subtypes of, for example, moving or lying in bed, and may thus be preferable for a full 24-hour recording.

<u>Sensor placement</u>

A variety of sites have been used in actimetry and accelerometry. Some of these were rather arbitrarily selected positions where actometer devices could be fastened easily such as at the wrist or ankle. Other sites were preferred because they were conventionally used for recording the electromyogram from prominent muscles, for example, the flexor carpi ulnaris muscle (forearm), or the peroneus muscle (lower leg). The flat design of today's accelerometers permits the placement of sensors on many parts of the body, even on the distal phalanx of the finger. The terminology is inconsistent across laboratories (Table 1 and Figure 1). We suggest the descriptive terms vertical, sagittal (x-direction), lateral (y-direction), and vertical (z-direction) instead of anatomical terminology referring to the craniocaudal, anterioposterior and mediolateral axes.

| Table 1 and Figure 1 |
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The present study is an extension of the previous investigations. A comparatively large number of subjects, a standard protocol containing 13 conditions and repeated three times, a five-sensor accelerometry, and the refined hierarchical classification should allow a reliable evaluation of this methodology and the derivation of especially valid sensor configurations. The aim of the study is to propose a standardization that will be suited to many future research applications.

## Method

### Participants

In this study, 31 male university students (age range = 20-32 years, M = 25.1 SD = 3.2 years) served as paid voluntary participants. The participants were told that the study would investigate various measures to assess physical activity. Informed consent was obtained.

### Apparatus

The Vitaport 2 (Becker Ingenieurbüro, Karlsruhe, Germany) was used for the multichannel recording. Vitaport 2 is a general purpose digital recorder/analyzer (32 bit microprocessor, 16 MHz) with minimized dimensions and power consumption designed for prolonged ambulatory recording. It weighs 700 g. The recorder is carried in a padded bag worn on a belt at the waist. The universal module includes eight analog input channels (16 kHz at 12 bit A/D), with software programmable amplifier gain, and high and low pass filter. Storage is available on 16 MByte RAM and 260 (or

170) MByte disk. The post-processing is carried out on Vitagraph Software (Jain et al., 1996) or add-on analysis programs developed by the user.

<u>Accelerometry</u>

The sensors (IC Sensor Model 3031) were piezoresistive, light-weight. They have wide bandwidth (i.e., DC and AC response), high sensitivity ~ 1 mV/g (standard range ± 2 g), and a typical accuracy of ± 0.2 %. The frequency response was practically linear up to the kHz range. The sensors (supplied by Vitaport, Becker Ingenieurbüro, Karlsruhe, Germany), were mounted, 20 x 20 x 2 mm, and weigh 4 g.

Each sensor was calibrated for a specific Vitaport2 amplifier channel by measuring the signal under controlled inclination, that is, by rotating the sensor providing a signal output corresponding to + 1 g and - 1 g (the gravitational constant) or 0 repectively 180 gedgrees to the gravitational axis. The DC output is zero when the sensitive axis is perpendicular to the gravitational axis. The recordings were obtained with a 32 Hz sampling rate and low pass filtering at 20 Hz.

The sensors were used as follows:

- Sternum. Three uni-axial sensors were placed adjacently at the sternum about 5 cm below the jugulum, the sensitive axes pointing in a (1) vertical, (2) sagittal, and (3) lateral direction, that is, in the z-, x- and y-direction, respectively.
- Thigh. Frontal aspect of (4) right and (5) left thigh, distal from m. rectus femoris, about 5 cm above the patella, the sensitive axes pointing in sagittal direction ((((besser ?? The sensitive axis of the sensors was roughly perpendicular to the surface, that is, to the frontal aspect of the sternum and the frontal aspect of the thigh??)))).

The sensors were fastened with adhesive medical tape (Fixomull® Stretch, Beiersdorf AG, Hamburg). The flexible cables were also fixed to the skin. All connections lead centripetally to the trunk (Vitaport recorder).

Procedure

After electrodes and sensors were attached and checked, the following standard protocol was carried out in a fixed order, each condition lasting for at least 40 seconds:

Block A

- Sitting, upright, palms on thighs or on table top,
- Sitting, leaning forward about 20 degrees from upright position,
- Sitting, leaning backward about –45 degrees from upright position.

Block B

- Standing, arms hanging down with palms to thigh.

Block C

- Lying, left side, legs slightly bent, left hand under the head, right hand on thigh
- Lying, legs and arms outstretched
- Lying, right side, legs slightly bent, right hand under the head, left hand on thigh,
- Lying, back supported, knees flexed, soles placed flatly on the bed.

Block D

- Walking, at normal pace
- Walking, at fast pace

Block E

- Stairs up once (60 step staircase, 6 landings)
- Stairs down once (same ??)

Block F

- Cycling (Ergometer 60 Watt), leaning forward, hands resting on handlebar.

This procedure, that is, the standard protocol, was the same for each subject. For each of the following three repetitions a permutation of Blocks A to F was conducted (see Table 2).

Table 2

Data analysis

Filtering

DC and AC components of the raw signal were separated by means of a first order FIR digital filter with a cut-off frequency at 0.5 Hz (3 dB). Raw signal, DC-values, and rectified AC-values were averaged across data points for each condition and monitoring segment. Walk frequency was calculated by means of short-time Fourier transform within the frequency band of 0.5 to 4 Hz using the z- (vertical) axis of the sternum sensor (Fahrenberg et al., 1997; Foerster et al.,1999; Qian & Cheng, 1996).

Hierarchical classification of posture and motion patterns

Data segments were classified by referring to the standard protocol variable profiles. Similarity is determined by the so called $L_1$ distances (see, e.g., Halmos, 1950). The $L_1$ distance between two conditions j and k with the variables i=1...nv is defined as

(1) $\quad dist_{jk} = \Sigma_{i=1...nv}|x_{ij} - x_{ik}|$

Unlike the $L_2$ distance (Euclidian Distance) $\sqrt{\Sigma_{i=1...nv}(x_{ij} - x_{ik})^2}$, which makes an adjustment for the risk of variables with large differences, in the $L_1$ distance the large and small differences are treated equally.

Whenever the variables used have different scalings (e.g., AC and DC variables) they have to be standardized. The most common standardization factor is the standard deviation as used, for example, for the z-transformation. In our investigation, however, we used a standardization factor which is suitable for the $L_1$ distance, namely the average absolute differences between the ns standard protocol conditions: for variable i we formulate:

(2) $\quad s_i = \Sigma_{j=1...ns}\Sigma_{k<j}|x_{ij} - x_{ik}|/[ns(ns-1)/2]$

This factor is a measure of discrimination of variable i between the ns standard protocol conditions (or a respective subset of them). Hence, the standardized $L_1$ distance is given by

(3) $d_{jk} = \Sigma_{i=1...nv}|x_{ij} - x_{ik}|/s_i$

Each of the standard protocol conditions represents a point in the nv-dimensional space given by the nv variables. A certain data segment m was labeled according to the standard protocol condition j to which it was nearest, that is, whose $L_1$ distance $d_{jm}$ was the smallest under the ns standard protocol conditions.

Hierarchical classification was conducted with a SAS© datastep macro using subsequent subsets of variables to discriminate subsets of conditions. Table 3 summarizes the steps denoting variables and standard protocol situations used.

| Table 3 |
|---|

After determining posture (lying, sitting, standing) and motion (yes/no) on the basis of discrimation (1) and (2), lying was categorized in detail by (4), and, if the subject was in supine position, by (5); sitting by (6); walking on the level and up stairs by (3), and, if walking was selected, by (7); and, finally, bicycle by (8). This classification procedure was applied to the three sets of repeated behaviors, that is, 39 (3 x 13) conditions, and to the monitoring outside the laboratory.

Besides the complete five-sensor configuration a two-sensor strategy was explored, as a minimum strategy. Two sensors, sternum z-direction and thigh x-direction, should suffice to distinguish general classes of postures and motions, that is, sitting, standing, lying, and moving, whereby subtypes of behaviors would be disregarded.

## Results

An almost perfect concordance was found between the behavior protocol in the laboratory and the classification based on calibrated accelerometry with a five-sensor configuration (Table 4). The $\chi^2$ (144, N = 31) = 13.47 and Cramer's coefficient V = 0.97 were highly significant and substantial. The overall agreement is impaired only by 38 (3.2 %) misclassifications; most of these discrepancies concerned the discrimination between sitting upright/leaning backward and the discrimination between dynamic activities, that is, walking, and climbing stairs.

| Table 4 |
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The findings obtained with the two-sensor configuration, that is, z-direction of the sternum sensor and x-direction of the right thigh, are shown in Table 5. Since the sternum sensor x-direction (sagittal) and the y-direction (lateral) were disregarded, subtypes of walking, of sitting, and of lying could not be distinguished. The agreement for classes of lying, standing, moving, and sitting, was almost perfect indicating only 1.3 % misclassifications.

| Table 5 |
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## Discussion

The findings indicate that the methodology based on calibrated accelerometers is nearly perfect in assessing motion and posture. As compared to the previous investigation (Foerster et al., 1999), the percentage of misclassifications could be reduced.

The increase in effectiveness of the assessment was probably due to refinements in this methodology. First of all, one more sensor is used and a three-axial recording from the sternum placement could be therefore included. The previously used four-sensor configuration was sternum, wrist, thigh, and lower leg. Secondly, the classification method (see Table 4) was refined to allow for a hierarchical procedure, instead of the previously used strategy of simultaneously comparing patterns and selecting the reference pattern with the smallest distance to label a certain segment.

However, such evaluation should also take into account essential differences in the study design. Previously, the effectiveness of accelerometric detection of behaviors was evaluated against behavior observation in the field Foerster et. al., 1999). The uneven distribution of naturally occurring behaviors over the contingency table may have impaired the conclusiveness of the findings. This consideration was decisive in designing the present study so that an equally distributed selection of behaviors in experimentally permutated order was included.

The present investigation was successful in distinguishing walking and climbing stairs and also, body rotation in lying position.

As regards the present study, there was neither heart rate nor a direct measure of energy expenditure available. Otherwise, it would be possible to evaluate the relationship between accelerometric variables and other indices of metabolism. Like the amplitude of the AC-component sternum and thigh (see Fahrenberg et al., 1996; Myrtek et al., 1996), the pace and the vigor of stride, as defined here, appear to offer promising data, too.

It should be mentioned, that a number of specific factors may affect the reliability of accelerometric assessments. It is basically supposed that the sensitive axis of the sensor in the x-direction must be perpendicular to the surface in order to provide reliable measurement. The precise placement of a sensor, for example, on the frontal aspect of the lower leg, is rather difficult. This would require a splint or small wedge to ensure the adequate fixation of the sensor. Therefore, this placement seems to be cumbersome. At other sites such as the sternum, the individual morphology may present difficulties for correct positioning. According to Bussmann (1998), the deviation from the geometric axis should not be greater than 15 degrees (corresponding here to 0.26 g). However, the relative sensor sensitivity depends on the orientation of the sensor and the cosine function of this relationship exhibits a minimum at 0 degrees and 180 degrees and a maximum at 90 degrees inclination. The placement of two sensors near to each other and with two different axes (x- and z-direction or x- and y-direction) could reduce the effect of a less precise placement because maximum sensitivity for the two axes will be present at different phases of movement.

It should be noted that the precise placement of sensors is essential when thresholds are used for the classification of motion. A classification that is based on individual reference patterns appears to be less susceptible to such deviations in threshold values. In any case, a careful positioning and fixation is an essential aspect of this methodology.

The DC-component of an accelerometer signal may be affected by temperature drift and in the long run by the aging of electronic components. However, within an 24-hr monitoring such off-sets will have rather small influence ((((effects)))) if a reference-pattern classification based on the standard protocol is used.

Two essential issues still have to be discussed. Would a smaller number of sensors suffice to obtain an equally correct classification? Which placements can be recommended?

Three sensor configurations are proposed based on the present findings. While a <u>two-sensor configuration</u> may suffice to assess the four basic classes of sitting, standing, lying, and moving, more sensors are required to distinguish subtypes of moving. This would require at least three sensors or, for increased reliability of discrimination, a <u>four sensor configuration</u>. With a <u>five-sensor configuration</u> 13 motion patterns and postures can be detected as shown in the present study. The quantification of hand tremor, for example, or the kinematic analysis of hand and arm movement, requires additional sensors on the dorsal aspect of the hand. Thus, according to the specific aims of an assessment, an adequate selection can be made.

| Table 6 |
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In the choice of the classification procedure, there are several arguments in favor of a hierarchical classification using individual reference patterns. This methodology appears to be especially appropriate for these assessments because of the large interindividual variability and the multivariate patterning of posture and motion.

In conclusion, the present findings on the valid detection of motion patterns and posture by calibrated accelerometry, suggest a standardization of this methodology. The two aspects are the sensor configuration (sites of placement) and the classification procedure. There are several points in favor of a hierarchical classification using individual reference patterns.

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Table 1: Axes and planes

| | Terms | Direction with reference to gravitational axis (Sternum vertical) |
|---|---|---|
| 1 | sagittal<br>anterioposterior<br>XXXXXXXXXXXXXX<br>(pointing forward) | x |
| 2. | lateral<br>mediolateral<br>horizontal<br>(pointing sideways) | y |
| 3. | vertical<br>craniocaudal<br>longitudinal<br>(pointing up) | z |

Note: Positive direction means that a positive signal is obtained when, for example, a three-axial sensor placed onto the sternum of the standing subject indicates movement up, forward, sideways.

Table 2: Permutation of blocked conditions

| Subjects | Standard | Repetition 1 | Repetition 2 | Repetition 3 |
|---|---|---|---|---|
| 10 | ABCDEF | CFBDEA | DFCBEA | ECDBAF |
| 10 | ABCDEF | DFCBEA | ECDBAF | CFBDEA |
| 11 | ABCDEF | ECDBAF | CFBDEA | DFCBEA |

Table 3: Hierarchical classification

| Step | Specification | Discrimination between Conditions (number of conditions) | Variables/Sensors used | Standardization necessary |
|---|---|---|---|---|
| 1 | Posture | lying (4), sitting (3), standing | DC of 3 sternum, 2 thigh | no |
| 2 | Motion | all | AC of 3 sternum, 2 thigh | no |
| 3 | Stairs | walking (2), stairs (2) | AC and raw signal of 2 sternum (sagittal, vertical), 2 thigh, walk frequency | yes |
| 4 | Lying | lying (4) | DC of sternum lateral | no |
| 5 | Supine | lying on back, supine | DC of sternum sagittal and vertical | no |
| 6 | Sitting | sitting (3) | DC of sternum sagittal and vertical | no |
| 7 | Walking | walking (2) | walk frequency | no |
| 8 | Bicycle | sitting forward, bicycle | AC of sternum sagittal, 2 thigh | no |

Table 4: Comparison of true and detected motions and postures (five-sensor configuration)

| Condition | Detected by Accelerometry | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | Total |
| 1 Sitting upright | 77 | 3 | 12 | – | – | – | – | – | – | – | – | – | – | 92 |
| 2 Sitting, leaning forward | – | 92 | – | – | – | – | – | – | – | – | – | – | – | 92 |
| 3 Sitting, leaning backward | – | – | 91 | – | – | – | – | 1 | – | – | – | – | – | 92 |
| 4 Standing | – | – | – | 91 | – | – | – | – | – | – | – | 1 | – | 92 |
| 5 Lying, left side | – | – | – | – | 92 | 1 | – | – | – | – | – | – | – | 93 |
| 6 Lying on back | – | – | – | – | – | 92 | – | 1 | – | – | – | – | – | 93 |
| 7 Lying, right side | – | – | – | – | 1 | – | 92 | – | – | – | – | – | – | 93 |
| 8 Lying supported, knees up | 2 | – | 1 | – | – | – | – | 89 | – | – | – | – | – | 92 |
| 9 Walking normal pace | – | – | – | 1 | – | – | – | – | 89 | 1 | – | 1 | – | 92 |
| 10 Walking fast pace | – | – | – | – | – | – | – | – | 1 | 90 | – | – | – | 91 |
| 11 Upstairs | – | – | – | – | – | – | – | – | 3 | 2 | 87 | 1 | – | 93 |
| 12 Downstairs | – | – | – | – | – | – | – | – | 3 | 1 | – | 89 | – | 93 |
| 13 Cycling | – | 1 | – | – | – | – | – | – | – | – | – | – | 91 | 92 |
| Total | 79 | 96 | 104 | 92 | 93 | 93 | 92 | 91 | 96 | 94 | 87 | 92 | 91 | 1200 |

Note: The accelerometric data obtained for the 13 conditions of the standard protocol were used as an individual reference pattern for the classification of the subsequently conducted three permutations of these conditions (3 x 31 = 93 classifications for each condition, 9 missing data). The contingency table had a $\chi^2$ (144, N = 31) = 13.47, $p < .001$. Cramer's V = 0.97.

Table 5: True and detected motions and postures (two-sensor configuration)

| Condition | Detected by Accelerometry Sitting | Standing | Lying | Moving | Total |
|---|---|---|---|---|---|
| Sitting | 276 | – | – | 3 | 279 |
| Standing | 1 | 91 | 1 | – | 93 |
| Lying | 3 | – | 367 | 1 | 371 |
| Moving | 2 | 4 | 1 | 457 | 464 |
| Total | 282 | 95 | 369 | 461 | 1207 |

Note: The accelerometric data obtained for the 13 conditions of the standard protocol were used as an individual reference pattern for the classification of the subsequently conducted three permutations of these conditions (1207 classifications, 2 missing data). The contingency table had a $\chi^2$ (9, $\underline{N}$ = 31) = 3459.7, $\underline{p}$ < .001. Cramer's $\underline{V}$ = 0.98.

Table 6: Proposed sensor configuration for standard accelerometric detection of posture and motion patterns.

| Number of sensors | Placement | Direction of axis | Suited for detection of |
|---|---|---|---|
| 2 | Sternum | z | Basic classes: Sitting, Standing |
| | right Thigh | x | Lying, and Moving |
| | | | (pace and vigor of stride) |
| 4* | as above, and | | |
| | Sternum | x | Subtypes of Sitting and Moving |
| | left Thigh | x | (Walking, Climbing stairs, Cycling) |
| 5 | as above, and | | |
| | Sternum | y | Body rotation in bed |

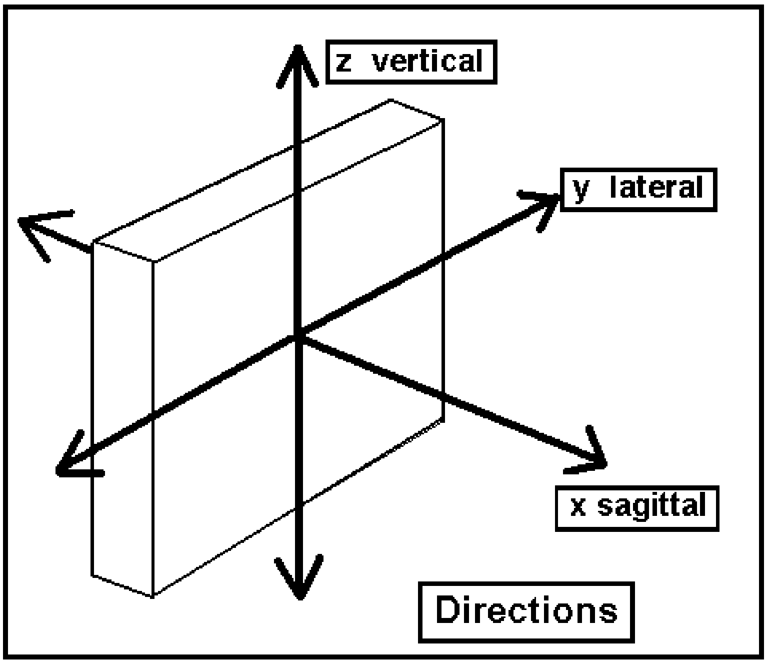
Note: * Recommended for optimal discrimination

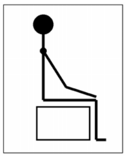
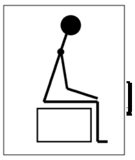
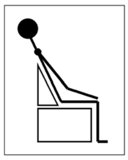
Figure Legends

Figure 1 : The x-, y- and z-direction of sensitvie sensor axes

(Figure 1 is an adjunct to Table 1)

Figure 2 : Postural and activity conditions


z vertical
y lateral
x sagittal
Directions

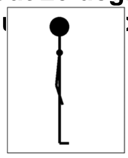




Sitting upright, palms on thighs or on table top

leaning forward about 20 degrees from u[illegible]osition

leaning backward about –45 degrees from upright position

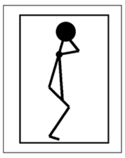
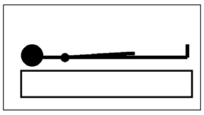
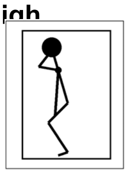
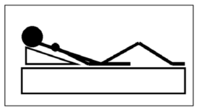
Block B



Standing with palms to thigh

arms hanging down

Block C

Lying

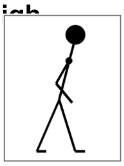
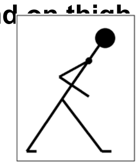
left side, legs slightly bent, left hand under the head, right hand on thi[illegible]

back, legs and arms outstretched

right side, legs slightly bent, right hand under the head, left hand [illegible]

back supported, knees flexed, soles placed flatly on the bed

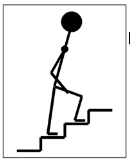
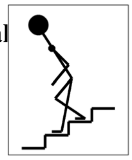
Block D

[illegible]ng at normal

at fast pace

Block E

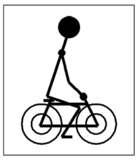



Stairs

up, 60 step staircase

down, 60 step staircase

Block F



Cycling

Ergometer 60 Watt, leaning forward, hands resting on handlebar