EVOLUTION OF ACTIVITIES OF DAILY LIVING USING INERTIAL MEASUREMENTS: THE LUNCH AND DINNER ACTIVITIES

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Abstract

In the context of designing eHealth services for *fragile* people, we propose to monitor Activities of Daily Living (ADL) in order to anticipate the potential loss of autonomy by behaviour changes. Nowadays, the availability of non-stigmatising sensors such as inertial sensors embedded on Smartphones allows the estimation of people's postures in real time in order to evaluate their autonomy in daily life. Our aim is to propose an unconstrained and non-intrusive method based on inertial sensors, which gives an indicator about a person's autonomy. This method determines the correlation between people's postures and activities over time in order to compute an index of ADL (*IndexADL*), specific to each person. The *IndexADL* variation over time is then a useful feature for positively or negatively evaluating people's autonomy. Our experiment, based on data collection of eight elderly people over a 3-month period, analyses the *Lunch* and *Dinner* activities with promising performances.

Keywords: ADL; inertial data; actigraphy; fragile people; activity index

Introduction

Tracking Activities of Daily Living (ADL) is very challenging but necessary to evaluate life quality and people's autonomy. Numerous studies on ADL monitoring are emerging with different approaches, which can be classified as wearable[1-4] and environmental systems.[5-8] Wearable systems are often judged more suitable for *fragile* people because of their cost and their reliability. On the contrary to environmental systems, Smartphone-based systems are non-stigmatising and non-intrusive solutions. In this study, inertial sensors embedded on a Smartphone were used to estimate people ADLs. These ADLs may be featured by using actigraphy method, which consists on the definition of individual posture sequences over a period of time. We investigate a new method based on long-term observations to discover and prevent loss of autonomy. The main contribution of our study is how to estimate ADLs evolution over time without imposing sensor positions and gesture learning phases. Our system builds, on a daily basis, an index of ADL (*IndexADL*), whose deviations may predict behaviour troubles or changes, which may alert family members and health professionals about the person's autonomy.

The aim of this study is to describe lunch and dinner index activity.

Methods

A specific ADL reference is determined for each person, leading to the development of an *IndexADL* for certain times of day. This personal ADL reference allows automatic assessment of a person's autonomy without any supervised learning phases or expert interventions. This study builds this ADL reference from unsupervised data. During the first 15 days, inertial data are filtered and then the sensor attitude is estimated in order to provide several personal posture profiles, called *posturograms*, which constitute one individual's ADL reference. (Figure 1)

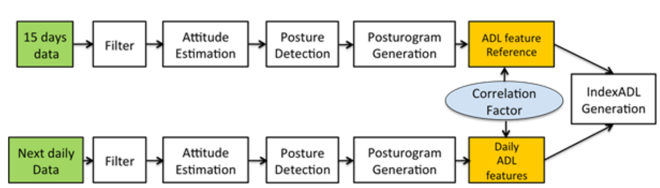

Figure 1. Main steps for generating IndexADL values.

The same process is reproduced for next daily data to generate ADL features. Thereafter, personal autonomy is evaluated by computing the *IndexADL* deviation and comparing the current daily ADL features to the individual ADL reference. Each of the processing steps is described.

Filtering Accelerometer Data

Accelerometer data are often noisy. Data processing is then needed to filter signal information. Two filters are applied: a high pass filter in order to detect only the dynamic phases,[9] and a classical low pass filter to ignore the gravitation acceleration influence.

Attitude Sensor Estimation

In order to define our ADL reference and to have comparable data, it is necessary to get measurements from a common frame. Therefore, we chose a relative frame related to the human chest to firstly preserve the body dynamic and to be close to the body's centre of gravity. The idea is to estimate the attitude with respect to the new frame using quaternion representation and then to compute new measurements in the chest frame. As proposed by Madgwick et *al*.[10] we computed a filter designed for pedestrian navigation using inertial data.

Posture Detection

We focussed on five postures: lying down, standing, sitting, walking and transfers. The first three are static postures and the last two are dynamic phases.

Posture detection is based only on accelerometer data, focusing on X and Z axes after sensor attitude estimation. We use the following rules:

- *Lying down*: detecting that a person is lying down is performed by considering the accelerometer orientation with respect to the gravity forces. The vertical accelerometer component is around zero.
- *Standing*: the vertical accelerometer component is around *g*. This posture always occurs before and after a walking period.
- *Sitting*: the vertical accelerometer component is around *g*. This posture never occurs before and after a walking period.
- *Walking*: among dynamic phases, walking period is identified as an interval of at least 3 successive human steps. Successive peaks with a frequency between 0.6 Hz and 2.5 Hz define a walking step.
- *Transfers*: transfers are characterised as non-walking dynamic phases. They include some transitions between two postures as summarised in Table 1.

Posturogram Generation

After detecting individual postures, we build one *posturogram* per day and individual from a learning phase of 15 days. A *posturogram* is a chart containing the posture succession during time. (Figure 2)

Table 1. Posture Transfers.

	Lying	**Sitting**	**Standing**	**Walking**
Lying	Yes	Yes	No	No
Sitting	Yes	Yes	Yes	No
Standing	No	Yes	Yes	No
Walking	No	No	No	Yes

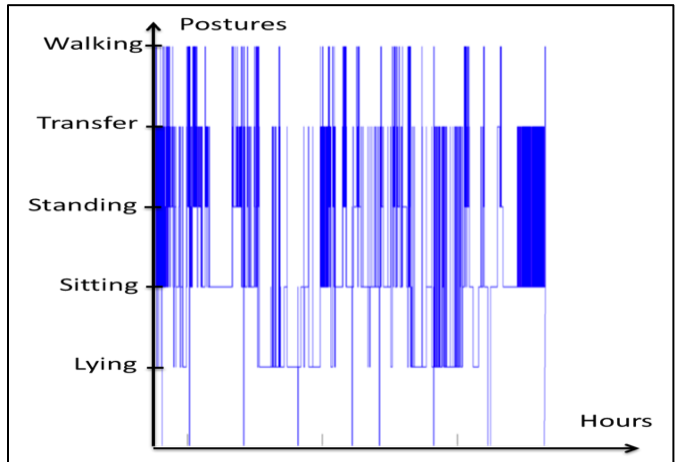

Figure 2. User 3 *posturogram* for one day.

ADL Feature Reference

This step concerns the determination of the ADL reference from individual *posturograms*. For this purpose, a statistical study is carried out. For each ADL, we segment specific periods of time for which we compute the posture repartition. Then, we obtain posture sequences composing the individual ADL reference, which is synthesised in a shape of a matrix. Matrix lines represent ADL variables and matrix columns contain posture repartition during the learning phase.

IndexADL Generation

The main objective of the ADL reference is to draw a posture profile for each person and for each ADL. This profile is based on the mean and standard deviation (SD) of posture repartition values computed during the learning period for a specific ADL. Thus, we create one user profile per posture for each ADL and build an index value, called *IndexADL* for each day. Therefore, personal autonomy can be evaluated by computing the offset between the daily *IndexADL* and his/her *IndexADL* historic.

As shown with dashed lines in Figure 3, we determine a compliance factor Δi by projecting the daily mean of the user posture repartition on his/her posture profile for each posture type. The global *IndexADL* concentrates all compliance factors of all postures and is given by:

$$IndexADL = 100 - \frac{1}{n_p} \sum_{i=1}^{n_p} \Delta_i \,, \qquad (1)$$

with n_p the number of postures. The *IndexADL* value can be directly interpreted. If it is close to 100 then the person behaves as usual. However, if the value is low, a loss of autonomy is detected. Moreover, the time evolution of this index allows anticipating situation changes.

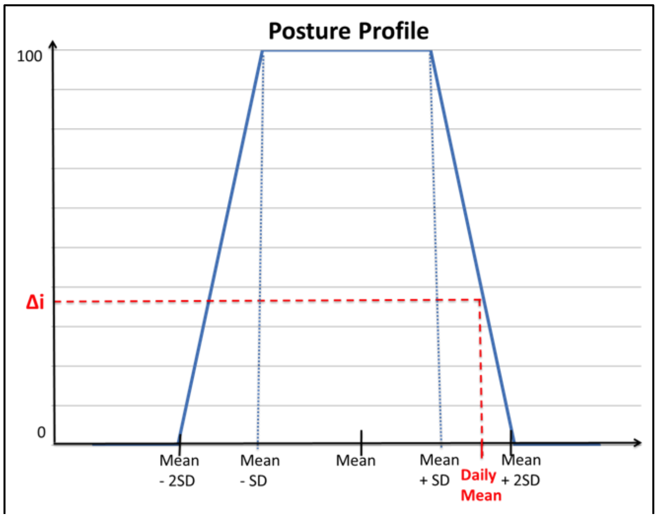

Figure 3. One posture profile based on the mean and the standard deviation (SD)

We collected inertial data on Smartphones equipped with a tri-axial gyroscope, a tri-axial accelerometer and a tri-axial magnetometer.[11] Eight people, (3 male, 5 female), aged 64 to 90 years old (mean age 76 years old) were recruited over a three month period. An Android application was used to capture data at a frequency of 30 Hz. This value was chosen as a compromise between the autonomy of the telephone and the amount of data necessary for the posture analysis.[12] All participants were compliant and regularly wore their Smartphone.

Results

IndexADL Evaluation on the Lunch and Dinner Activities

In this study, we focussed on the Lunch and Dinner activity of the first six participants. Thanks to subjective data collected during the experiments, lunch and dinner times were known, enabling us to select inertial data from these specific beginning and ending instants of time. As presented, our method filtered the selected
inertial data and then estimated the sensor attitude. Then, posture detection gave time repartitions for all postures during the lunch and dinner time every day. The first 15 days serves as an ADL reference. For the next following days, IndexADL values were calculated with regard to mean and standard deviation values, computed on the Lunch and Dinner ADL references.

Figure 4 shows Lunch IndexADL evolutions for the first six participants over 30 days. It was observed that IndexADL values may vary from 22 to 100 but more interestingly trend lines reveal people's autonomy regarding this Lunch activity. When drawing trend lines, we observe global IndexADL variation, which was interpreted as three categories:

- Firstly, stationary trend lines reveal good people autonomy during the experiment with few variations between days, describing no crucial behaviour changes. User 1, User 2 and User 4 were in this category;
- Secondly, increasing trend lines represent people who may have had some difficulties or changes during their Lunch activity in the beginning of the experiment, but show autonomy gain in the last week. User 5 and User 6 were in this situation;
- Thirdly, decreasing trend lines show participants with a loss of autonomy during time. User 3 is in this less positive situation.

Figure 5 shows Dinner IndexADL evolutions for six participants for a period of 30 days. It is interesting to note that similar situations appear for the Dinner activity. Consequently, some punctual autonomy degradations may reveal an isolated issue, but decreasing trends on a long observation period may alert assistance services.

Conclusions

A new design for an ADL detection system based on inertial data is presented in this paper. Our main contribution is to build an original index revealing a person's autonomy without any preliminary learning behaviour pattern or restriction on the sensor position. The proposed method uses postures identification and creates a personal reference. The IndexADL is a good indicator about people's autonomy for the Lunch and Dinner activities and may anticipate behaviour changes. Considering the promising preliminary results in the present study, we intend to evaluate more

ADLs in future works. Likewise, other studies on larger datasets must be realised to confirm these preliminary results.

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Figure 4. Lunch *IndexADL* evolutions for 6 participants.

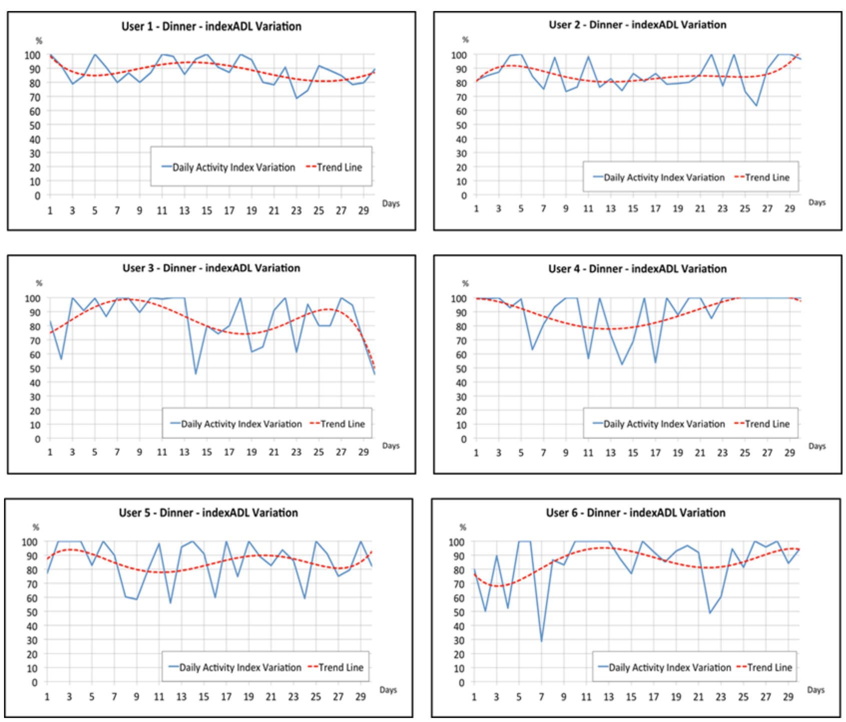

Figure 5. Dinner *IndexADL* evolutions for 6 participants.

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Conflict to interest. The authors declare no conflicts of interest

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