A Public Domain Dataset for ADL Recognition Using Wrist-placed Accelerometers

Conference Paper · August 2014

DOI: 10.13140/2.1.4355.9687

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***Abstract*— The automatic monitoring of specific Activities of Daily Living (ADL) can be a useful tool for Human-Robot Interaction in smart environments and Assistive Robotics applications. The *qualitative* definition that is given for most ADL and the lack of well-defined benchmarks, however, are obstacles toward the identification of the most effective monitoring approaches for different tasks. The contribution of the article is two-fold: (i) we propose a taxonomy of ADL allowing for their categorization with respect to the most suitable monitoring approach; (ii) we present a freely available dataset of acceleration data, coming from a wrist-worn wearable device, targeting the recognition of 14 different human activities.**

I. Introduction

The automatic monitoring of specific Activities of Daily Living (ADL), adopted in gerontology for the assessment of the independence level of a person, is among the most active research fields of Ambient Intelligence [1]. By providing information about human behaviour, an automated system for its recognition can be a useful tool for both Human-Robot Interaction (and cooperation) in smart environments [2] and the purposes of Wearable and Assistive Robotics [3].

In the literature, two families of approaches have been explored: on the one hand, *smart environments* rely on heterogeneous sensors distributed in a monitored area and adopt a top-down approach to infer the person status from the context [4]; on the other hand, *wearable sensing systems* rely on sensors located on the person body and adopt a bottom-up approach to imply the person status from limb movements [5]. A literature analysis allows for the identification of some pivotal concepts:

- smart environments are the preferred approach to monitor complex sequences of activities, subject to timing constraints and requiring interaction with various objects and household appliances [6];
- wearable sensing systems making use of acceleration information are quickly becoming the preferred approach to monitor either body gestures or bio signals [7].

Nonetheless, since ADL have been envisaged for a *qualitative* performance evaluation carried out by qualified medical staff, two challenges remain to be solved: (i) there is still no established set of criteria for the representation of ADL in terms of measurable quantities; (ii) there are still no well-defined benchmarks for the comparison of different approaches. In an effort toward the development of standard metrics for the quantitative description of ADL we propose a taxonomy of ADL allowing for their categorization with respect to the most suitable monitoring approach. Furthermore, as a simple benchmark for different wearable sensing systems, we present a public dataset of acceleration data targeting the recognition of 14 different human activities.

The article is organized as follows: Section II reports a literature analysis on ADL and human activities monitoring systems; Section III details the proposed taxonomy of ADL and the presented public dataset for wearable sensing systems is described in Section IV; conclusions follows.

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II. Background

A. Activities of Daily Living

Since the publication of the *Index of Activities of Daily Living* (1959) by Katz and colleagues for the classification of the functional status in elderly people, the process of determining the level of autonomy of a person has been usually accomplished by analysing their ability in carrying out a set of daily activities, each one involving the use of different motor and cognitive capabilities [8]. An informed caregiver would ask the elderly to perform each activity (either at home or at an appropriate facility) and manually classify them as *independent* (2 points), as *requiring assistance for specific tasks only* (1 point) or as *requiring assistance* (0 points). By summing the points obtained for each individual ADL a person level of autonomy can be assessed on a scale ranging from "A" (i.e., independent) to "G" (i.e., totally dependent).

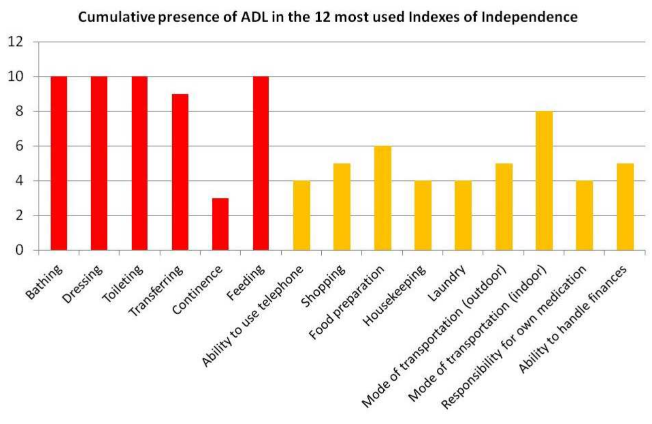

Fig. 1. Cumulative presence of ADL in 12 of the most used Indexes of Independence: most indexes rely on a subset and/or a combination of Katz Index (red columns) and Lawton and Brody Index (yellow columns).

The activities considered in Katz index (see the red columns in Figure 1) address basic person needs exclusively, aiming at the mere survival of the person. With the intent to grasp also the more complex aspects that characterize a healthy and independent life, the *Lawton and Brody Scale of Instrumental ADL* [9] introduces the concept of *Instrumental ADL* (IADL), which focus on the usage and interaction with devices and tools of common use. The proposed IADL are reported in the yellow columns in Figure 1. Other commonly adopted indexes aim at: (i) a simplification of the assessment procedure and the development of self-rating systems [10], [11], [12]; (ii) the validation of Index systems in terms of the relation between ADL scores and self-rated health [13], [14]; (iii) the validation of Index systems in terms of the relation between ADL scores and cognitive functionalities, as a useful tool to monitor the progress of dementia [15], [16], [17], [18], [19].

As the Figure shows, the number of ADL considered by the reported commonly adopted indexes of independence is relatively small and it can be expressed as a subset and/or a combination of Katz ADL and Lawton and Brody IADL.

B. Automatic Monitoring of ADL

Existing systems for the automatic monitoring of ADL can be classified with respect to the adopted *sensing strategy* in three families of approaches.

- *Smart environments*. Heterogeneous sensors are distributed throughout an environment purposely modified in advance [4]. This approach is typically undertaken when a *soft* monitoring is sufficient or when a person health conditions do not allow for or explicitly forbid the use of wearable devices (e.g., people suffering from severe cognitive impairments).
- *Wearable sensing*. Sensors are located on the person body using wearable devices or purposely engineered articles of clothing [1], [5]. Since sensors are physically carried around, the monitoring can virtually occur in any place. However, issues related to obtrusiveness and privacy may limit their applicability in the real world.
- *Hybrid approach*. When allowed by the application scenarios, it is often convenient to merge the two previous approaches. The integration between smart environments and wearable devices is an active and challenging research trend [20].

Wearable sensing, in particular, has risen in recent years to become the most commonly adopted strategy for monitoring simple human activities. Most systems aim at engineering a single device, either based on a single or more types of sensory information [21]. Among the solutions following the first approach, systems based on a single tri-axial accelerometer are the most common. As outlined in [1], they share a similar architecture, whose main tasks are as follows.

1) To extract relevant *features* from the available sensory data. On the one hand, features should allow for the creation of robust representations of the activities (i.e., allowing for small variations among executions); on the other hand, they should require limited computational time and resources for on-line extraction and processing. Gravity and body acceleration are the most commonly adopted features [22].
2) To create representations of the target activities in terms of the considered features.
3) To classify the run-time data according to the available representations.

The representation of target activities, and the corresponding classification of run-time sensor data, is typically either based on the definition of *rules* and the adoption of decision trees [22] or on the creation of *models* (e.g., Hidden Markov Models or Gaussian Mixture Models) and the definition of adequate distance measures [23].

In spite of the reported similarities between most wearable sensing systems presented in the literature, it is still very difficult to identify which ADL can be effectively monitored with such systems and which are the best solutions, due to the lack of standard ADL descriptions in terms of measurable quantities and the lack of public benchmarks. In the following Sections, we address both these issues.

III. Taxonomy of ADL for Automatic Monitoring

It is possible to design an effective system for the automatic assessment of the health status of a person only if a number of conditions are met, namely:

1) there exists a finite number of activities that allow for a qualitative evaluation of the health status of the person;
2) activities are expressible in terms of measurable quantities, that can be monitored by an automatic system.

ADL satisfy the first requirement. Unfortunately, the purely qualitative definition that is given for most of them poses great challenges for their expression in measurable quantities, i.e., the second requirement, and lead to many different interpretations of the same ADL. As an example, let us consider the *feeding* ADL: its possible quantitative descriptions range from a single temporal procedure focusing on person location and household appliances status [24], to a set of simpler motions, such as “pouring water”, “drinking”, “using fork and knife”, monitored by wearable sensing systems [7]. Figure 2 reports a taxonomy of ADL aiming at

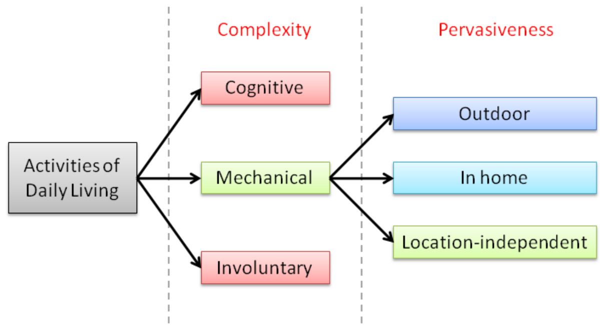

Fig. 2. Taxonomy of ADL for automatic monitoring.

the identification of the most suitable monitoring technique for each activity. The categorization of ADL is achieved with respect to two parameters, namely:

- **complexity** analyses the cognitive abilities required for the execution of the activity and allows for a discrimination between: (i) unconscious motions; (ii) mechanical

actions and sequences of mechanical actions; (iii) activities requiring high-level cognitive capabilities;
- **pervasiveness** analyses the requirements on the context posed by the activity for its execution and allows for a discrimination between: (i) activities that happen on a wide area and require interactions with unknown external entities; (ii) actions that only happen at specific locations and require interactions with a-priori known external entities; (iii) actions that are independent from the context and can be executed anywhere.

On the basis of the complexity criteria, it is possible to classify the ADL listed in Figure 1 in three categories.

- **Cognitive** ADL (e.g., *responsibility for own medication*, *ability to handle finances*) are complex activities for which the mechanical execution of a sequence of actions is not enough to infer the correct execution of the ADL. The automatic monitoring of cognitive ADL requires sensing and reasoning capabilities far beyond those of most state-of-the-art ADL recognition systems and is an interesting challenge for future research.
- **Mechanical** ADL are activities that can be decomposed in a sequence of actions whose mechanical execution guarantees their correctness. For example, the *feeding* ADL is defined by the sequential execution of drinking and eating actions, that can be further decomposed in lower level motions, such as picking up and putting down a glass. Most state-of-the-art monitoring systems can effectively detect a number of mechanical ADL.
- **Involuntary** ADL (e.g., *continence*) are highly-specific and highly-localized basic body functions that can only be monitored by ad-hoc systems.

Let us consider the *transferring* ADL, which refers to postural transitions such as sitting on/standing up from a chair: this motion does not require a monitoring system with advanced reasoning capabilities, since its detection is sufficient to infer the correct execution of the ADL. Conversely, the *responsibility for own medication* ADL, referring to one's ability of following medical prescription, requires a monitoring system able to detect mechanical actions, extract their meaning and compare them with the prescription rules to infer whether the ADL has been correctly executed.

On the basis of the pervasiveness criteria, mechanical ADL can be further classified in three categories.

- **Outdoor** ADL (e.g., *shopping*, *mode of transportation outdoor*) are complex activities that take place in a theoretically unbounded area outside of the person house (or the monitored area). We argue that outdoor ADL can be best monitored with smartphones, since they allow for the coverage of wide areas and can rely on widespread and standardized technologies for the acquisition of information from external sources.
- **In home** ADL (e.g, *bathing*, *food preparation*, *housekeeping*, *laundry*) are complex activities that only take place in purposely-designed rooms and require the interaction with specific objects and devices. As it is shown in literature, smart environments allow for the effective and reliable monitoring of in-home ADL [20].
- **Location-independent** ADL (e.g, *dressing*, *toileting*, *transferring*, *feeding*, *ability to use telephone*, *mode of transportation indoor*) are motions that can virtually take place anywhere and are best (and more often) monitored with wearable sensing systems [1].

Using a reduced set of adopted sensors and methodologies, it is already possible to envisage benchmarks for the comparison of different wearable sensing systems aiming at the detection of location-independent ADL.

IV. Public Dataset Description

We present a public dataset[1] for the recognition of location-independent ADL with wearable sensing systems.

The dataset is composed of 979 trials, referring to the 14 motions listed in Table I and collected from 16 volunteers (11 men and 5 women, with age ranging from 19 to 81 and mean of 57.4 - the large age range of the participants allows for the creation of a wider dataset, that is not targeted to one specific purpose). Each trial records the tri-axial acceleration values registered during one execution of one motion.

Hardware specifications. In all recordings we used a small ad-hoc sensing device (40 mm $\times$ 22 mm $\times$ 12 mm) equipped with a single tri-axial accelerometer. The accelerometer has a measurement range of $[-1.5g; +1.5g]$ mapped to $[0; +63]$ with a sensitivity of 6 bits per axis. The sampling frequency is 32 Hz. The device is firmly attached to the right wrist of the user and its orientation is shown in Figure 3.

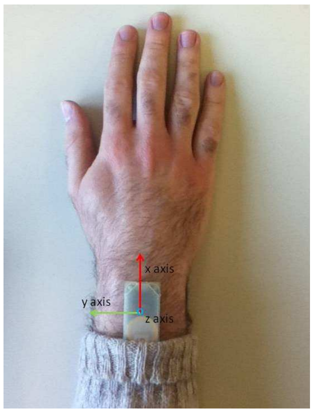

Fig. 3. Position of the tri-axial accelerometer on the right wrist of a person.

Acquisition procedure. All the trials were recorded at the homes of the volunteers, in a series of supervised experiments. A volunteer, equipped with the device, is asked to perform one of the motions of interest and the supervisor labels the corresponding acceleration data as an execution of the motion. To increase the naturalness of the executions, in each session the supervisor defines which motions are to be performed and the number of repetitions, varying with the motion and the volunteer, while the volunteer is allowed to choose which motion to perform each time.

[1]The dataset and its detailed description are freely available at: `http://archive.ics.uci.edu/ml/datasets/Dataset+for+ADL+Recognition+with+Wrist-worn+Accelerometer`

TABLE I

LOCATION-INDEPENDENT ADL AND MOTION PRIMITIVES

ADL	Motion primitive
Toileting	Brush own teeth Comb own hair
Transferring	Get up from the bed Lie down on the bed Sit down on a chair Stand up from a chair
Feeding	Drink from a glass Eat with fork and knife Eat with spoon Pour water into a glass
Ability to use telephone	Use the telephone
Mode of transportation (indoor)	Climb the stairs Descend the stairs Walk

Human motion primitives. To ensure the repeatability of experiments, we break ADL down into the low-level activities which we call "human motion primitives" (HMP). HMP are motions that uniquely identify an activity and are associated with stereotyped movements. Table I lists the HMP that we considered for each monitored ADL. In the following, we define each of the HMP listed in Table I as:

- **simple** (i.e., different people executing the HMP generate similar acceleration patterns), as opposed to **complex** (i.e., different people executing the HMP generate highly different acceleration patterns);
- **full-body** (i.e., the HMP involves the motion of the lower limbs), as opposed to **arm-only** (i.e., the HMP involves the motion of the upper limbs exclusively);
- **recursive** (i.e, the acceleration data generated by the execution of the HMP has a recursive pattern), as opposed to **non recursive** (i.e, the acceleration data generated by the execution of the HMP does not have a recursive pattern).

Each HMP is associated to a pair of figures: the image on the left depicts a volunteer executing the motion, the image on the right reports the corresponding acceleration pattern. The axes of abscissae measure time, while the axes of ordinates report, from top to bottom, the acceleration recorded on the x axis, on the y axis and on the z axis of the accelerometer.

We consider the *toileting* ADL as composed of (at least) two HMP, having complex, arm-only, non-recursive acceleration patterns, that can be distinguished from other activities for their frequency spectrum content.

- *Brush own teeth* refers to a person brushing their teeth with a toothbrush held in the right hand, as shown in Figure 4 (a) and (b).
- *Comb own hair* describes a person who brushes their hair with a brush held in the right hand, as shown in Figure 4 (c) and (d).

The *transferring* ADL is composed of (at least) four HMP.

- *Get up from the bed* is the motion executed by a person who is initially lying on a bed and then gets up to a standing posture, as shown in Figure 5 (a) and (b).

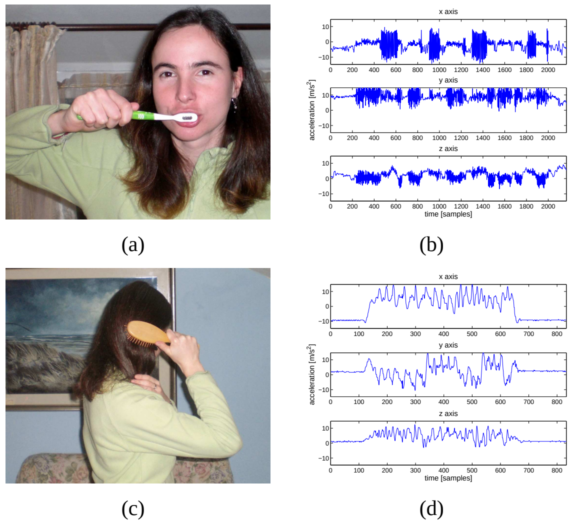

Fig. 4. *Toileting* ADL: (a), (b) refer to the HMP *brush own teeth*; (c), (d) refer to the HMP *comb own hair*.

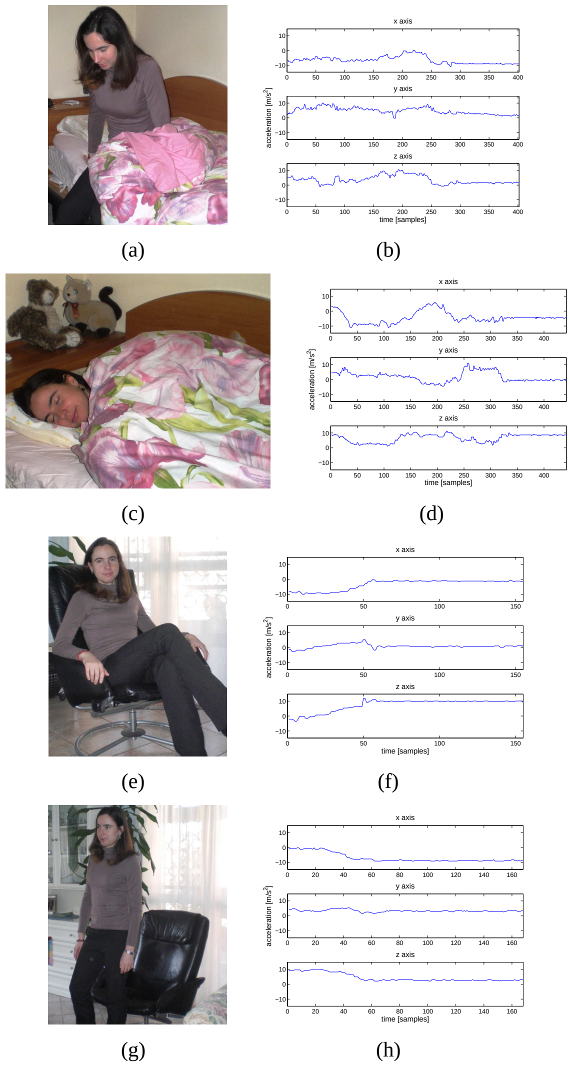

Fig. 5. *Transferring* ADL: (a), (b) refer to the HMP *get up from the bed*; (c), (d) refer to the HMP *lie down on the bed*; (e), (f) refer to the HMP *sit down on a chair*; (g), (h) refer to the HMP *stand up from a chair*.

- *Lie down on the bed* is the motion executed by a person standing beside a bed, who then lies down on it, as shown in Figure 5 (c) and (d).
- *Sit down on a chair* refers to a person who is standing in front of a chair and then sits down on it, as shown in Figure 5 (e) and (f).
- *Stand up from a chair* is the motion of a person who is at first sitting on a chair and then stands up, as shown in Figure 5 (g) and (h).

Motions referring to the *transferring* ADL have simple, full-body, non-recursive acceleration patterns, that report the change of orientation of the accelerometer with respect to gravity. We developed a system for the detection of *transferring* HMP that models their gravity and body acceleration components and subsequently computes distance metrics between the on-line data and the models [7], [23].

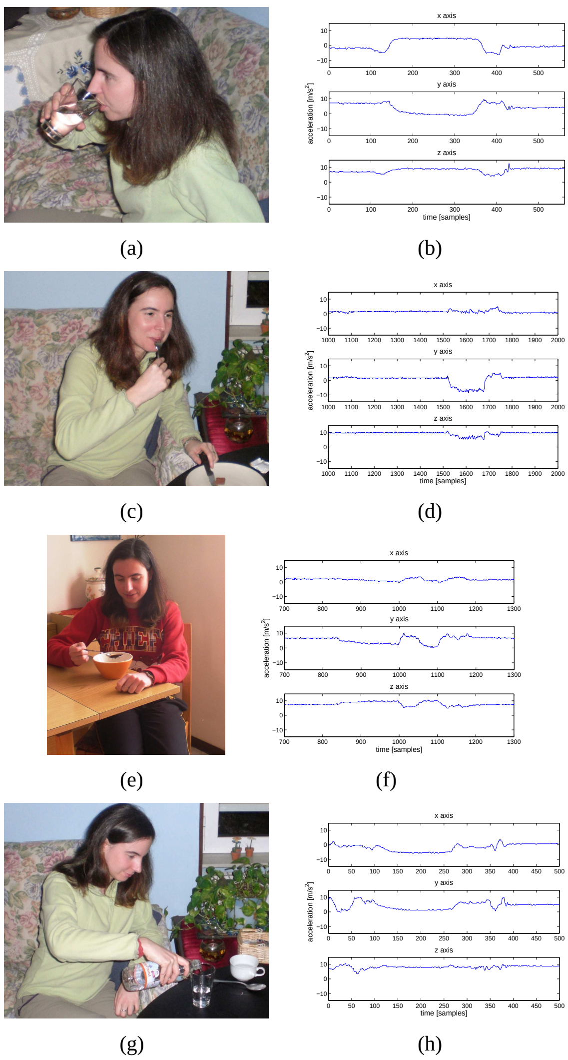

Fig. 6. *Feeding* ADL: (a), (b) refer to the HMP *drink from a glass*; (c), (d) refer to the HMP *eat with fork and knife*; (e), (f) refer to the HMP *eat with spoon*; (g), (h) refer to the HMP *pour water in a glass*.

The *feeding* ADL is defined by (at least) four HMP, which have complex, arm-only, recursive acceleration patterns.

- *Drink from a glass* refers to a person sitting at a table who: (i) grasps a glass on the table and lifts it to mouth level, (ii) drinks, (iii) puts the glass back on the table, as shown in Figure 6 (a) and (b).
- *Eat with fork and knife* comprises the sequence of motions of a person who is sitting at a table holding a fork in the right hand and a knife in the left hand. Then they: (i) cut a piece of meat and hold it with the fork, (ii) lift it to mouth level, (iii) eat, (iv) lower the fork again, as shown in Figure 6 (c) and (d).
- *Eat with spoon* describes a person sitting at a table with a spoon in the right hand who: (i) lowers the spoon to fill it, (ii) lifts it to mouth level, (iii) eats, (iv) lowers the spoon again, as shown in Figure 6 (e) and (f).
- *Pour water in a glass* refers to a person who: (i) grabs a bottle from a table with the right hand, (ii) pours some of its content in a glass on the table, (iii) puts the bottle back on the table, as shown in Figure 6 (g) and (h).

Due to the variable length and procedural structure, further decomposing these HMP in simpler motions (e.g., "picking up", "putting down") may increase the recognition accuracy.

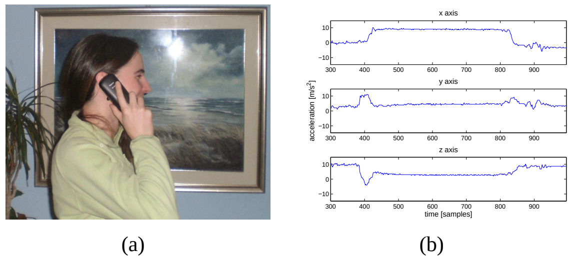

Fig. 7. *Ability to use telephone* ADL.

The *ability to use telephone* ADL is the HMP referring to a person who is standing and: (i) grabs the telephone, (ii) lifts it to face level, (iii) talks, (iv) puts the telephone back in its holder, as shown in Figure 7. The corresponding acceleration pattern is simple, arm-only, non-recursive.

The *mode of transportation indoor* ADL is composed of (at least) three HMP, which have simple, full-body, recursive acceleration patterns and are the motions more often and more reliably monitored with wearable sensing systems.

- *Climb the stairs* refers to a person climbing up a number of staircase steps, as shown in Figure 8 (a) and (b).
- *Descend the stairs* depicts a person going down a few staircase steps, as shown in Figure 8 (c) and (d).
- *Walk* represents a person taking a number of steps, as shown in Figure 8 (e) and (f).

V. Conclusions

We propose a taxonomy of the ADL listed in Katz Index and Lawton & Brody Index allowing for their categorization with respect to the most suitable monitoring approach. Considering the cognitive abilities required by a correct execution of the activity we classify ADL as *involuntary*, *mechanical* or *cognitive*. Mechanical ADL can be further classified according to the requirements on the context as *outdoor*, *in home* and *location-independent*. We argue that smartphone-based systems could be reliably used for the detection of

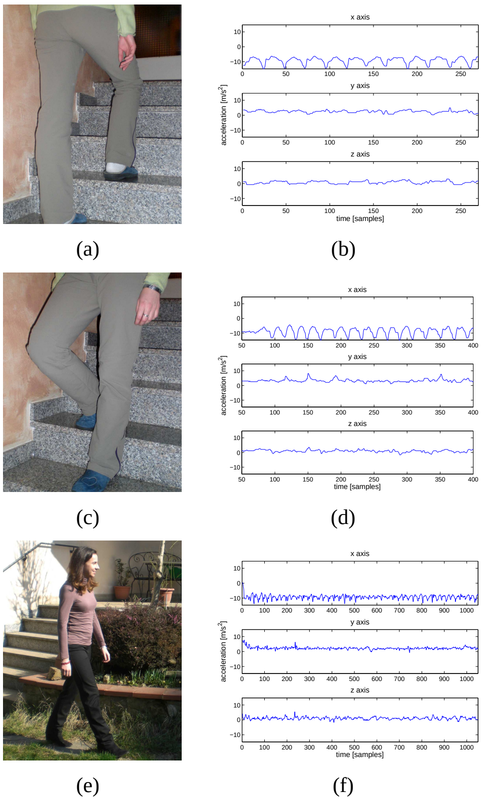

Fig. 8. *Mode of transportation (indoor)* ADL: (a), (b) refer to the HMP *climb the stairs*; (c), (d) refer to the HMP *descend the stairs*; (e), (f) refer to the HMP *walk*.

outdoor ADL, while smart environments are the preferred option for in home ADL and wearable sensing systems allow for an effective monitoring of location-independent ADL.

We also present a publicly available dataset of accelerometer data targeting the recognition of 14 different motions referring to location-independent ADL. Current work focuses on an extension of the dataset to include activities and motions that are proper of human-human and human-robot interaction, that we hope will open interesting research scenarios in the industrial context of shared human-robot workspaces. Future work will further extend the dataset by considering: (i) intra-class variations for the listed HMP; (ii) handedness of the volunteers; (iii) HMP requiring the coordinated use of both hands. We hope that this work will contribute to the definition of benchmarks for the comparison of wearable sensing systems and that it will foster the research in the field of human activity recognition.

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