Multi-sensor data fusion techniques for the identification of activities of daily living using mobile devices

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Abstract. This paper presents a PhD project related to the use of multi-sensor data fusion techniques, applied to the sensors embedded in mobile devices, as a mean to identify user's daily activities. It introduces some basic concepts, such as the definition of activities of daily living, mobile platforms/sensors, multi-sensor technologies, data fusion, and data imputation. These techniques have already been applied to fuse the data acquired with different sensors, but due to memory constraints, battery life and processing power of these devices, not all the techniques are suited to be used in these environments. This paper explains an overview about the state of the research in this topic, explaining the methodology to create a best effort method to recognize a large number of activities of daily living using a mobile device.

Keywords. Sensors; data fusion; multi-sensor; mobile platforms; activities of daily living

1 Introduction

The identification of Activities of Daily Living (ADL) focuses on the recognition of a well-known set of everyday tasks that people usually learn in early childhood. These activities include feeding, bathing, dressing, grooming, moving without danger, and other simple tasks related to personal care and hygiene. On the context of Ambient Assisted Living (AAL), some individuals need particular assistance, either because the user has some sort of disability, or because the user is elder, or simply because the user needs/wants to monitor and train his/her lifestyle.

The aim of this PhD research consists in the definition of a set of ADLs that may be reliably identified with mobile devices. This includes the activities related to acquire data and recognize a set of tasks and identify which tasks are accurately recognized.

The joint selection of the set of valid sensors and the identifiable set of tasks will then allow the development of a tool that, considering multi-sensor data fusion technologies and context awareness, in coordination with other information available from the user context, such as their agenda and the time of the day, will allow to establish a profile of the tasks that the user performs in a regular activity day.

The accuracy of the identification of ADLs using a mobile device depends on the environment where the data is acquired, the methods used in data processing/imputation/fusion, and the mobile devices used. Several pattern recognition and machine learning techniques have already been used for the identification of ADLs. Besides, data collected can have noise, and statistical methods should be applied to minimize it. Hence, the algorithms for the detection of ADLs can be improved to increase the set of activities that can be accurately detected using mobile devices.

As a result of this PhD a new method to recognize a large set of ADLs with mobile devices will be developed and implemented.

This paper is organized as follows. Section 2 presents a review of the state of the art, focusing in the main concepts of this topic. Section 3 introduces the proposed solution to be developed during this PhD work. Section 4 presents the discussion and conclusion.

2 Related Work

This research topic involves many different areas of research: activities of daily living, multi-sensor, data fusion and data imputation. This section reviews previous works in these areas but constrained to the use of mobile devices.

2.1 Identification of activities of daily living

Activities of daily living (ADL) are activities that require more than just the necessary cognitive and physical abilities but a sense of personal identity and awareness response of others. These activities involve a desire to achieve a degree of physical comfort, self-care, and autonomy, which promotes feelings of independence and personal control [1]. Common activities of daily life are related to personal appearance and hygiene, domestic skills, household management, family and child care, family planning and sexual matters, budgeting and personal administration, conversational and social skills, mobility transfers, and leisure, education, training and work activities [1]. The detection of health problems, using the analysis of ADLs, is carried out by the analysis of the accuracy of the patient when performing these activities. In [2] is shown that detection of ADLs may assess how life's quality of people with dementia is affected. The evaluations of ADLs involve some psychological or medical determinations to understand people's ability to care for themselves on a day-to-day basis [3].

A variety of sensors have been used to recognize ADLs. Accelerometer, door, item, temperature, light, wearable, gravity, ECG, vital sign and RFID sensors, GPS receivers, microphones, cameras, and other sensors, are used to detect when a person is having/preparing a meal, washing up, bathing, waking up, sleeping, standing, sitting, watching TV, using the phone, doing the chores, cycling, jogging or perform other activities [4-20].

2.2 Mobile Platforms

Mobile devices are used in the vast majority of people's daily activities [21]. These devices are embedded with a large variety of sensors [22], such as GPS receiver, accelerometer sensor, gyroscope sensor, proximity sensor, light sensor, communication sensors, acoustic sensors, digital camera and other over-the-air sensors.

The mobile platforms available in the market in 2014 [23] are Android, iOS, Windows Phone, BlackBerry, Samsung Bada, Samsung Tizen, Symbian, MeeGo, Asha, Firefox OS, and Ubuntu Touch. The two platforms responsible for the largest market share are Android and iOS operating systems [24].

2.3 Multi-Sensor

The use of multiple sensors may increase the reliability of the system. The most important stage in multi-sensor systems is signal classification with pattern recognition or machine learning methods [25].

Multiple sensors can be used in the detection of ADLs or monitor rehabilitation activities. In [26] a system, which combines different sensors, was created for data processing and logging. In [27] a human-aided multi-sensor fusion system was created. It involves the integration of the Probabilistic Argumentation System and the Structural Evidential Argumentation System, which both are variants of the Dempster-Shafer belief function theory. Detection of ADLs are carried out in [28] by using a platform composed of a base station and a number of sensor nodes, recognizing human activity with the minimum body sensor usage through the use of dynamic sensor collaboration. In [29] a wearable multi-sensor ensemble classifier for physical activity pattern recognition was developed, which combines multiple classifiers based on different sensor feature sets to improve the accuracy of physical activity type identification and recognizing 6 different physical activities. In [30] wearable inertial sensors and fiber sensors attached to different human body parts are used to capture kinetic data. Recognition is achieved by combining it neural networks and hidden Markov models.

In [31] a wireless wearable multi-sensor system was created for locomotion mode recognition, with three inertial measurement units (IMUs) and eight force sensors, measuring both kinematic and dynamic signals of human gait, using a linear discriminant analysis (LDA) classifier.

2.4 Data Fusion

Data fusion consists in the integration of data and knowledge from several sources [32]. According to [33, 34], data fusion methods belong to three categories. These are:

- Probabilistic methods (Bayesian analysis of sensor values, Evidence Theory, Robust Statistics, and Recursive Operators);
- Probabilistic approaches (Least square-based estimation methods such as Kalman Filtering, Optimal Theory, Regularization, and Uncertainty Ellipsoids and Bayesian approach with Bayesian network and state-space models, maximum likelihood methods, possibility theory, evidential reasoning and more specifically evidence theory);
- Artificial Intelligence (Intelligent aggregation methods such as Neural Networks, Genetics Algorithms, and Fuzzy Logic).

Multiple techniques related to sensor fusion are presented in [32, 34-36], using several sensors and techniques, such as Kalman filter and their variants, neural networks and other statistical methods.

2.5 Data Imputation

During acquisition time data collection can fail in some instants. These failures may be due to various reasons. Missing data failures can be classified as [37, 38]:

- Missing completely at random (MCAR) happens when missing values are randomly distributed across all observations;
- Missing at random (MAR) is the condition that exists when missing values are randomly distributed within one or more subsamples instead of the whole data set like MCAR;
- Missing not at random (MNAR) is the type of missingness that arises when missing values are not randomly distributed across observations.

However, various methods exist for the estimation of missing values in what is called Data Imputation.

Several methods related to data imputation are presented in [39]. The main methods are K-nearest neighbors and other statistical methods [39-41]. For the recognition of ADLs, some methods can be applied in pattern recognition and health state detection [39, 42, 43]. During this PhD other statistical algorithms will also be studied.

3 Proposed Solution

The proposed solution to solve the problem presented in section 2 consists in the design and development of different methods/algorithms for the automatic identification of a suitable set of ADLs using sensors embedded in off-the-shelf mobile devices. Identification will be supported with other contextual data, e.g. the agenda of the user.

The solution proposed in this PhD work for the identification of ADLs is composed of different modules/stages (figure 1):

- Sensors data acquisition;
- Sensors data processing;
- Sensors data fusion;
- Sensors data imputation;

- Data Mining/Pattern Recognition/Machine Learning techniques.

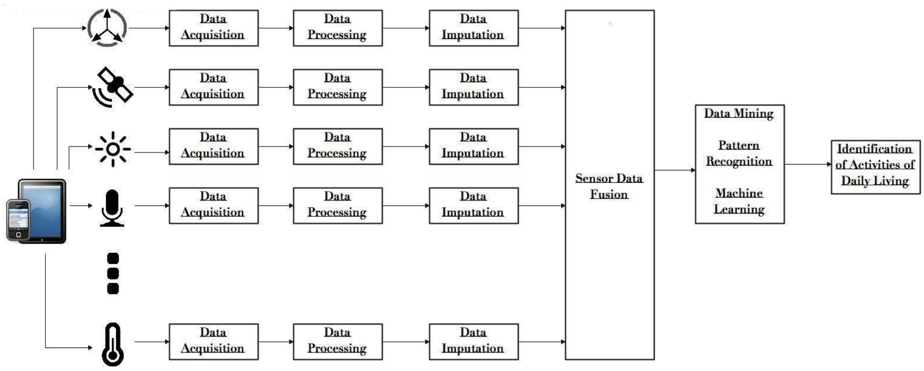

Fig. 1. Process for the identification of Activities of Daily Living using mobile sensors

The first stage 1 includes the research to determine the sensors that the system should use in order to identify accurately a large set of ADLs. Sensors that are available in mobile devices differ depending on the mobile platform used and hardware, but they are commonly those mentioned in Section 2.1.

Data acquisition process, which it is the second stage of the proposed solution, should be adapted to the environment and positioning, related to the user's body, of the mobile device. Data collected is used in the Data Processing stage. This stage must use methods to minimize the effects of environmental noise in the data collected by all the available sensors and convert these data to homogeneous units. In the PhD thesis, a new method to commute the algorithm with the number of sensors available should be created.

Due to the different number of sensors available in mobile devices, a process is needed to analyze which are the sensors available in the used mobile device and determine the maximum number of sensors that should be used during data acquisition and data processing in order to increase the accuracy of the identification.

After data acquisition and data processing stages, data fusion deals with merging appropriately the data coming from all those sensors. Although this can be done with different methods, Kalman filter and their variants are the most commonly used with low processing techniques or with server side processing. The capacities of the mobile devices are the most important criteria for choosing one method for data fusion techniques. During this PhD project, a new method to carry out efficiently sensor data fusion with a mobile device will be developed. The main objective is that this data fusion stage occurs in real-time without large local processing, because the mobile devices have low processing capacities and memory.

Sometimes data acquisition can fail due to the unavailability of sensors, unknown errors occurred in real-time collection. This can affect the global performance of the system to recognize ADLs. Hence, the existence of a module for data imputation is very important. Data imputation techniques can be applied before or after sensor data fusion using different statistical methods. Missing data can be generated using several algorithms (*e.g.* K-nearest neighbor (KNN) schemes, likelihood-based schemes, Bayesian-based schemes and multiple imputation (MI) schemes) or other methods, such as MLE in multivariate normal data, GMM estimation, Predictive mean matching (PMM), Multiple imputation via MCMC and Multivariate imputation by Chained Equations. In this PhD project, the reliability of the existent methods will be verified and a new method for data imputation will be developed (if needed).

Next, pattern recognition or machine learning methods will be created for the identification of activities of daily living. They must be validated with a gold standard (*i.e.* inquiring a user about the activities performed or watching the user).

Finally, all these algorithms/methods will be implemented as a mobile application. The mobile application should be developed for a major mobile operating system in order to automatically detect the activities of daily living of a subject, with a comfortable degree of accuracy in different environments.

4 Discussion and Conclusion

Until now this PhD project has reviewed the state of the art of the different topics related to the identification of ADLs using a mobile. These are:

- Activities of daily living;
- Multi-sensor techniques;
- Sensors data fusion technologies;
- Sensors data imputation techniques;
- Mobile platforms;
- Context aware applications.

Currently, mobile devices, such as smartphones, tablets, among others are widely used. Mobile devices incorporate various sensors, depending on the platform used, which allow capturing a variety of data.

These sensors are able to detect different parameters about people's health, activities of daily living and other purposes. Sensors available in mobile devices are quite diverse, such as accelerometry sensors (*e.g.* gyroscope, accelerometer and magnetometer), acoustic sensors (*e.g.* microphone), location sensors (*e.g.* GPS receiver), digital camera and other over-the-air sensors (*e.g.* heart rate monitors).

This PhD project will use those sensors to identify activities of daily living. The study about the identification of activities of daily living is very complex and it is divided in some subtopics, such as multi-sensor, data fusion, mobile platforms, identification of activities of daily living and data imputation.

At this stage, a state of the art has been finalized in order to obtain the global knowledge to design and develop new methods for each one of those stages. Finally, all these methods will be embedded in a mobile application that will allow the validation with users under real conditions.

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