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Human Activity and Motion Disorder Recognition: Towards Smarter Interactive Cognitive Environments

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Abstract.
The rise of ubiquitous computing systems in our environment is engendering a strong need for novel approaches of human-computer interaction. Either for extending the existing range of possibilities and services available to people or for providing assistance the ones with limited conditions. Human Activity Recognition (HAR) is playing a central role in this task by offering the input for the development of more interactive and cognitive environments. This has motivated the organization of the *ESANN 2013* Special Session in *Human Activity and Motion Disorder Recognition* and the execution of a competition in HAR. Here, a compilation of the most recent proposals in the area are exposed accompanied by the results of the contest calling for innovative approaches to recognize activities of daily living (ADL) from a recently published data set.

1 Introduction

Decades of technological development have recently motivated the emergence of remarkable contributions in Robotics, Electronics and Computer Science, such as the invention of smarter environments, appliances and devices. These have been largely motivated by the intrinsic need of providing specialized and improved assistance to humans. For example, in healthcare recovery and wellbeing, safety, surveillance, home automation, and also military operations. Human intervention is needed in many systems for decision making, usually by means of interaction through traditional devices such as keyboards, remote controls, switches, or touchscreens. These mechanisms of human-computer interaction are becoming intractable considering the amount of devices we are exposed to every day.

We are now facing a new challenge as a result of the easy access to vast amounts of information coming from different sources (e.g. environmental and wearable sensors, portable computing devices and online databases) which can contribute to counteract our demanding interaction with machines, especially because we are always (involuntarily or not) providing feedback to the environment through our behavior and actions. For instance, physiological signals could be a indicator of an emerging health condition as an increase in our average daily heart rate or body temperature. Systems could therefore become more cognitive fundamentally transforming our ways of interaction with them [1].

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Human Activity Recognition is an active research field in which methods for understanding human behavior are developed by interpreting attributes derived from motion, location, physiological signals and environmental information, etc. This field is the first component (*Sensing*) of the sequence for achieving Smarter Interactive Cognitive Environments together with *data analysis*, *decision making* and *taking action* [2, 3], and our subject of research.

This paper is the introductory work for the *ESANN 2013* Special Session in *Human Activity and Motion Disorder Recognition: Toward Smarter Interactive and Cognitive Environments*. Here we introduce the main concepts behind Human Activity Recognition and their application into real world problems with particular focus on the fields of assisted living and motion-related human disorders. The current state of the art is also explored while incorporating the novel contributions from the Special Session. Additionally, a competition in HAR was concurrently organized with the session in which participants were encouraged to propose a learning method to perform the classification of activities of a newly published data set [4]. This contains the recordings from a group of individuals performing a set of ADL while wearing a waist-mounted smartphone with embedded inertial sensors. The best performing submitted approaches are similarly covered in this work.

1.1 The Structure of HAR Systems

A general representation of the human activity recognition process including its principal components is depicted in Figure 1. Many of the HAR approaches found in literature, including the ones for this Special Session, follow a regular structure with slight variations depending on their type of application, sensors, and selected Machine Learning (ML) algorithms. The diagram is valid to supervised [5], semi-supervised [6] and incremental learning approaches [7] differing on the type of input (labeled or unlabeled) and if the learned model updates when new samples are added into the system (notice the *Feedback* dotted line on the graph).

Moreover, traditional HAR systems usually operate in a feed-forward basis thus *Learning* is performed offline only once and there is no further feedback into the system. This is useful in cases where the data distribution does not change over time or the system is subject-independent and robust against high input variability. Otherwise adaptive methods such as incremental online or transfer learning [8] are advised but conditioned with an increase in the computational load into the process. In relation to the analysis of high level activities, which are combinations of simple activities (e.g. assembling furniture or fixing a car [9]), there is a minor amount of work that has been done and it is still an open research field.

Several approaches have been proposed in the literature for performing HAR: The work presented in [10] was pioneer in developing a method for the detection of a set of activities of daily living using five body-worn accelerometers and employing well-known ML classifiers. More recently in [11] human activities were classified using a smartphone-embedded accelerometer carried on the pocket in an attempt to simplify the recognition process with a more pervasive, practical and unobtrusive approach. In the same way other approaches can be found in [12, 13, 14].

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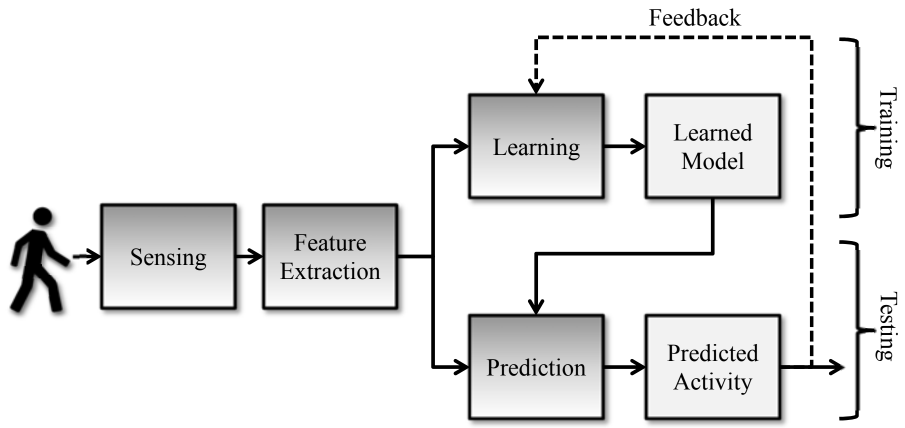

Fig. 1: The Human Activity Recognition Process Pipeline.

1.1.1 Sensing Devices

The right choice of sensors is one of the first elements to be taken into consideration for the design of HAR systems. They can be categorized by their sensing mechanisms: namely *external sensing* when sensors are in predetermined locations in the environment and *wearable sensing* when they are worn or attached to the body. A large range of devices have already been employed for HAR applications. Externally, presence sensors, microphones, video cameras [15], and recently 3D motion capture sensors such as the Microsoft Kinect [16] are commonly used. Their main limitation lies in their area of operation delimited by their static infrastructure. Video-based systems can be very effective for HAR but they are somewhat disadvantageous due to their demanding computations and privacy concerns, for instance, when used within home environments as people are generally uncomfortable about being continuously monitored. Additional video-based approaches can be found in [17].

Wearable sensors such as accelerometers, gyroscopes, heart rate monitors and thermometers partly solve these two previous issues but also bring new challenges: preserving battery life and minimizing obtrusiveness while being able to gather reliable context information from limited sensing. Furthermore recent mass-marketed portable computing devices are being manufactured with integrated sensors, initially designed for specific uses such as gaming and enriched user interfaces, they are now being also employed for HAR. This introduces a novel, pervasive and economic solution without additional hardware required and while also providing computing capabilities and wireless communications. A thorough review of wearable HAR solutions is presented in [12, 13].

In addition, hybrid approaches which combine wearable and external sensing from different sources, offer an alternative robust option for HAR. For instance, in [18] a sensor rich environment has been set for the collection of signals from 72 environmental

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and body sensors aiming to evaluate complex activities in an indoor location.

1.1.2 Experimental Setup and Data Collection

The definition of the experimental set up for data acquisition is also an important aspect in HAR. It should reproduce as close as possible the real conditions of the application it is intended for. *Naturalistic environments* are ideal for experimentation but in many cases it is not feasible to exploit them. Therefore controlled experiments can be carried out in laboratory conditions aiming to simulate natural settings (*semi-naturalistic environments*).

Failures in the design of HAR systems can be due to the lack of real life considerations such as unaccounted activities or target users, noise, sensor calibration and positioning, etc. This latter is for instance highly linked to the system performance as presented in [19, 20] where different sensor locations were evaluated for determining the ideal positions for performing HAR through the use of wearable accelerometers. Another final consideration about the experimentation process is the number of individuals selected as generally larger number of people involving various age groups and physical conditions are preferred. This is also directly related with the performance and generalization capability of the system in the presence of new users.

1.1.3 Feature Extraction and Selection

A reduced representation of the sensory input can be attained by selecting a significant set of features that will largely impact the discrimination ability of the learning algorithm. Therefore many aspects need to be considered for their selection. A traditional approach in HAR is the fragmentation of the sensor signals into time windows with a fixed length, which is application dependent. For example, for the recognition of body transitions such as *stand-to-sit* or *walk-to-run*, short time spans are required (in the order of seconds). But other complex activities such as motion disorders (e.g. detection of ON-OFF states in Parkinson's Disease (PD) Patients [21]) may require longer window lengths periods for ensuring certainty about the detection of a particular condition. It is also common to select overlapping windows (typically 50% [10]) as in this way it is possible to go through time events more smoothly. There are many features commonly used in literature [13] which are mostly obtained from the time and frequency domains, even though some other alternatives include wavelet transform coefficients which allow combined time-frequency signal representations.

The curse of dimensionality is certainly linked with the length of the feature vector selected and it can be detrimental for the performance and computational load of the recognition systems. Mechanisms for reducing the number of features come into light such as *feature selection* in which the features are evaluated with diverse metrics for determining and selecting the more informative subsets or *feature extraction* where the feature vector dimensionality can be diminished by performing inter-feature transformations whether through linear or non linear methods. Some HAR systems that have considered these mechanisms such as in [22, 23].

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1.1.4 Machine Learning methods

The automatic classification of human activity can be targeted using Machine Learning, generally by applying supervised learning algorithms although semi-supervised and unsupervised methods have also been proposed [24, 25]. Frequentist and Bayesian models have been well covered throughout HAR literature, they involve predictive models such as binary decision trees and threshold-based classifiers [26, 27], geometric approaches including K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN) and Support Vector Machines (SVM) [19, 28, 22], and probabilistic classification methods as for example Naïve Bayes classifiers, and Hidden Markov Models (HMM) [29, 30].

It is not fully clear which ML approach performs better for HAR as many of them have demonstrated comparable performance in different works (e.g. [12]). The optimal classification method is generally application-specific [31] and aspects such as the recognition performance, energy consumption, memory requirements and computational complexity become deciding factors. For instance decision trees could be preferred when the model interpretability is required and SVMs for high performance applications. Continuous work in regards to computational cost reductions have constantly been studied such as modified efficient implementations of the ML algorithms as proposed in [32], where a purely fixed-point arithmetic approach for HAR using SVMs was presented.

1.1.5 Evaluation Metrics and Performance

The evaluation of HAR classification algorithms is predominantly made through the statistical analysis of the models using the available experimental data. The most common method is the *confusion matrix* which allows representing the algorithm performance by clearly identifying the types of errors (false positives and negatives) and correctly predicted samples over the test data. Various metrics can also be extracted from the data such as model accuracy, precision, recall and F1-Score [13]. Lastly, other comparative measures between algorithms are prediction speed and memory consumption.

2 Contributions to the ESANN 2013 Special Session in Human Activity and Motion Disorder Recognition

The Special Session in *Human Activity and Motion Disorder Recognition* collected the research from 8 groups dealing with HAR related aspects. Topics extending from theoretical ML approaches to application-specific work were covered in the session. They were divided into two groups: The first one includes the studies on HAR application areas such as smart homes, driving safety, and motion disorder recognition for the elderly. The second group is related to the HAR Competition and collects the proposed methods for the classification of human activities of the released dataset (See Section 3). Each paper is briefly presented below.

HAR in smart homes is taking increasingly importance due to the need of providing safer and more responsive environments to people [33, 14]. In particular for the disabled and the elderly for health care and assisted living without the need of caretakers or family members. For example, the detection of anomalous behavior can be an indicator

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of an emerging health condition and the need of medical assistance. Some of these behaviors can be detected from the analysis of variations occurring while performing routinary activities throughout the day. For this reason, in [34] a method has been proposed for the long term analysis of daily activities and the detection of irregularities in the normal routine within a smart home. A two-step process predicts first 7 ADL such as showering, sleeping and having breakfast using an ANN. This is followed by the classification of daily routines into to normal, suspicious or unusual through a clustering algorithm. Their experiments were carried out using the Kasteren dataset [35] which use wireless environmental sensors in different house locations.

In contrast, wearable accelerometers have been located in different body locations (chest, waist, thigh and left under-arm) to determine the best performing sensors for the classification of 9 ADLs using decision tree analysis in [36]. Experiments were carried out with 8 people and obtained a variable performance ranging from 73.3% to 85.8%, being largely affected by the difficulty of detecting transitions such as *standing-sitting*. Results showed that sensor location is activity-dependent and that multi-sensor arrangements improve the recognition accuracy as expected. The sensor located on the thigh appears to be the most informative of all within the selected set of ADL. Similar works have also explored sensors posisioning using different sets of activities and/or applications [20, 37].

The third study [38] focused on driving safety and the detection of alcohol levels in car drivers. Several experiments were performed using a realistic car simulator software and a PC racing kit while blood alcohol content from volunteer drivers was being measured with a breathalyser and established as the ground truth. A set of environmental sensors located in the steering wheel and the pedals (force and position) were used to detect variations on the driving patterns and predict motion disorders. Results on classification accuracy showed a classification performance of 89.0% for the single-user approach and a 78.0% accuracy in the multi-user case showing their system is not fully subject-independent. They detected inebriated sujects using either an ANN or SVM binary classfier and also predicted alcohol levels through a SVM regression model. This application is an example of dealling with challenging environments where naturalistic experiments cannot be easily achieved as stated in 1.1.2 due to the risks that entail driving under the effects of alcohol in the real world.

In [39], specific work is being done to counterweight the alarming increase in the world's elder population while having limited caretaking resources available. They concentrate on Parkinson's Disease patients and the detection of motor problems such as dyskinesia, tremor, dystonia or bradykinesia and the prediction of ON-OFF periods in which the patients present or not the disease symptoms. The development of a large scale database for the evaluation of 100 patients within 5 countries was proposed in order to provide a reliable source of information for the monitoring and treatment of the disease. Two experimental directions are attempted in this project considering controlled and uncontrolled trials in a naturalistic setting which is each patient's home.

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Ref.	Approach Implemented	Accuracy
[40]	OVO Multiclass linear SVM with majority voting.	96.40%
[41]	Kernel variant of learning vector quantization with metric adaptation	96.23%
[42]	Confidence-based boosting algorithm Conf-AdaBoost.M1.	94.33%

Table 1: HAR Competition. Test error accuracy of the best performing approaches.

3 HAR Competition and Proposed Solutions

A competition targeting the development of novel learning approaches for the classification of a set of activities was planned as part of the special session. Competitors were challenged to submit their proposals given a new publicly available data set described in [4]. The HAR database was built from the sensor recordings of thirty subjects performing 6 ADL while carrying an Android OS smartphone with embedded accelerometer and gyroscope. A progressive description of the methodology employed for the experimentation with volunteers, signals processing and feature extraction was presented along with preliminary classification results obtained on the dataset by exploiting an SVM approach. Participants were provided with an unlabeled test set and the performance of their approaches was measured in terms of error accuracy using the experiment ground truth. The three best contributions are depicted in Table 1.

In [40], a One-Vs-One (OVO) Multiclass SVM with linear kernel was proposed for the classification task. The method used majority voting to find the most likely activity for each test sample from an arrangement of 6 binary classifiers. An overall accuracy of 96.40% was reached on the test data and this method became in the competition winning solution. For comparative purposes, they also evaluated the performance of a One-Vs-All (OVA) SVM and a KNN model which exhibited poorer accuracies (93.7% and 90.6% respectively). In the same way, a sparse kernelized matrix Learning Vector Quantization (LVQ) model was employed in [41] for the HAR data set classification achieving 96.23% test accuracy, only differing 0.17% against the first approach. Their method is a variant of LVQ in which a metric adaptation with only one prototype vector for each class was proposed. Ultimately, a novel confidence-based boosting algorithm (Conf-AdaBoost.M1.) was presented in [42] and assesed against the traditional decision tree classifier and the AdaBoost.M1 algorithm. The method is a direct multiclass classification approach which exploits confidence information from weak learners for the classification. They achieved an accuracy of 94.33% on the test set.

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