Cloud-based recognition of complex activities for ambient assisted living in smart homes with non-invasive sensors

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Cloud-based Recognition of Complex Activities for Ambient Assisted Living in Smart Homes with Non-Invasive Sensors

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***Abstract*—Automatic recognition of complex activities can aid in finding correlations between the daily habits of people and their health state, and can further lead to early detection of diseases or accidents. In this paper we propose a cloud-based system for recognition of complex activities by detecting series of atomic actions with non-invasive sensors. Collected data from non-invasive, non-intrusive and privacy preserving sensors is streamed into a cloud-based system, where automated feature extraction and activity recognition is performed. The prototype of the proposed system is evaluated with an experiment. Five activities performed by a person in a room were monitored by a sensor kit and streamed to the cloud, where the built classification models could recognize the activities with accuracy of 80% to 95%, depending on the length of segmentation windows which varied from 5 to 20 seconds, respectively.**

***Keywords*—ambient assisted living; smart homes; non-intrusive sensors; complex activities recognition**

I. Introduction

The average age of the population has been on the increase, especially in the developed countries. This trend has significant impact on health care systems [1]. Medical professionals believe that one of the best ways to detect an emerging medical condition before it becomes critical is to look for changes in the activities of daily living (ADLs). Systems that recognize ADLs from sensory data are now an active topic of research. Diverse approaches have been proposed to deal with the activity recognition problem, ranging from video cameras [2] to wearable sensors [3].

Installation of sensors in homes raises serious privacy concerns. In this paper we mitigate these issues by using non-invasive sensors that preserve the privacy of monitored individuals, do not interfere with their normal routines, and do not require wearing of sensors or tags. Furthermore, the proposed system streams the collected data into a cloud-based system, where it is first fused and then used for building classification models.

In the next section we describe the background and related work in the literature. In section III we present the system design, by first discussing the available non-intrusive sensors that can be employed for activity recognition in smart homes and then describing the feature extraction and selection process. Next we describe the experimental setup and then we discuss the obtained results by the proposed approach. Finally, section VI concludes the paper and describes our plans for future work.

II. Related work

Many activities however, involve complex physical motion and more interaction with the environment. A sensor system that can detect changes in everyday activities in the home could enable a new generation of home-based and institutionally-based services for the aging. Activities of interest fall into three categories: activities of daily living (ADLs), instrumental activities of daily living, and enhanced activities of daily living. ADLs are the primary daily personal care activities that are necessary for people to be able to live independently.

There are various ways for a computer to automatically acquire data about people's activities using sensor systems: ask the individual (as in experience sampling), remotely observe the scene using audio, visual, electromagnetic field, or other sensors and interpret the signal readings, attach sensors to the body and interpret the signal readings, and attach sensors to objects and devices in the environment and interpret the sensor readings [4].

Attaching sensors to the body is a promising and relatively inexpensive technique to acquire data about certain types of human movement. This techniques have been used to detect various activities such as walking, running sitting, standing and lying down [3], [5], [6].

In [7] is presented a system for recognizing activities in the home setting. The proposed sensing system presents an alternative to sensors that are sometimes perceived as invasive, such as cameras and microphones. The system combines electronic experience sampling, a set of small, easy-to-install, and low-cost state-change sensors to monitor the interaction of people with the environment, and supervised pattern classification algorithms to recognize everyday activities. Preliminary results on a small data set show that it is possible to recognize

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activities of interest to medical professionals such as toileting, bathing, and grooming, with detection accuracies ranging from 25% to 89% depending on the evaluation criteria used.

A health-care framework for supervising lifestyle diseases using long-term activity monitoring is proposed in [8]. This framework is hierarchical and comprises of three modules: activity recognition, activity pattern modeling and disease prediction. The activity recognition module is using embedded sensors-based activity classifier to recognize user's activity from the set of objects used in a period of time. The accuracy of classifying the activities is around 86%.

The authors in [9] have proposed a design and developed a platform to support remote monitoring, and an intelligent system to detect and predict anomalies in the patients with serious breathing problems. The goal of this platform is to detect simple symptoms such as shortness of breath using wearable sensors. This is one of the most common symptoms of several respiratory diseases such as emphysema, bronchitis and pleurisy and can be detected with breath amplitude sensors. Changes in the breath frequency and the body temperature can imply of problems and need of medical attention.

A framework for maintaining security and preserving privacy for analysis of sensor data from smart homes, without compromising on data utility is presented in [10]. Storing the personally identifiable data as hashed values withholds identifiable information from any computing nodes. Generalization and suppression on identifiers from the identifier dictionary before re-introduction could achieve different levels of privacy preservation.

Detection of ADLs can in turn lead to prediction of potential diseases. Even though there are a lot of studies aimed at detection of ADLs, most approaches have serious privacy concerns resulting from the types of sensors, use case or system design. In this paper we are proposing a system that relies on non-intrusive and privacy preserving sensors that passively collect data. Furthermore, the data is streamed to a cloud for several reasons: first, coping with the vast volumes of data originating from the sensors that require significant processing power, second, building collaborative models to enhance the system functionalities, and third, integration with other health care models.

III. System design

The premise is that activities which are normal for healthy persons, could occur more frequently in presence of some illness. Aiming to detect changes in behavior, a model from normal observations needs to be built. Later on, the normal pattern can be compared with new observations and the deviation can be estimated. Significant variations could indicate a change in the persons health state.

A. Architecture

We propose a cloud-based architectural design of the system, shown in Fig. 1. The sensors collect the data, and using Arduino Yun [1], it is streamed directly to the cloud services. This is an inexpensive and compact microcontroller board with an operating system based on Linux. The board has built-in Ethernet and WiFi support, a USB-A port, micro-SD card slot, 20 digital input/output pin. It is sufficiently versatile for connecting a variety of sensors to it, while being able to stream data to the cloud.

After the data is collected, the user identifier is not sent. Rather only the hash of the userid (which is a one-way transformation), sensor number (i.e. not a unique identifier of the sensor, rather a sequential number that identifies the sensor within a sensor kit), measurements of the sensors and timestamps. The hash value of the user could be used only in the cases when individual classsificaiton modes are to be built. Regardless, it is not used as feature for building the actual models. When buliding general models for all users, the hash value is not even required. This paired with the non-identifiable information nature of the data collected by the sensors, which are non-invasive and non-intrusive, ensures that the system has privacy-preserving properties.

Collecting and processing data that is generated at high frequency by diverse sources is a common challenge for many applications nowadays. Various technologies are being developed that can facilitate this task in a reliable and scalable way. Technologies like Apache Flume [2], Apache Kafka [3], or Amazon Kinesis [4] can be used as a messaging backbone that delivers incoming data streams to databases and stream processors. In our implementation, the Arduino Yun publishes data on an Amazon Kinesis data stream, which uses secure communication protocols.

The data fusion consists of parsing, formatting, time alignment and data-type mapping of the incoming data. After the data fusion, all data streams are unified into one stream.

Next, after the segmentation of data into windows, the feature extraction is performed. Approaches such as [11] can be employed for parallel extraction of features, whereas the feature selection can be efficiently performed with parallelized and distributed algorithms, such as [12], [13]. These methods can be executed on platforms such as Hadoop [14] and Apache Spark [15], on personal or public cloud-hosting platforms. Likewise, the classification models can be built with libraries that are already parallelized for the cloud, such as Random Forests, which are available in the scalable machine learning library Apache Spark MLlib [5]. Due to the size of the dataset used in our experiments, we have used only one on-demand Amazon AWS instance that can be scaled up or down. When the data volume increases and if the up-scaling on one instance is not enough, the cluster alternatives based on Hadoop can be used.

[1]https://www.arduino.cc/en/Main/ArduinoBoardYun, retrieved at 2017-01-15

[2]https://flume.apache.org, retrieved on 2017-01-15

[3]https://kafka.apache.org, retrieved on 2017-01-15

[4]http://docs.aws.amazon.com/streams/latest/dev/introduction.html, retrieved on 2017-01-15

[5]http://spark.apache.org/mllib/, retrieved on 2017-01-15

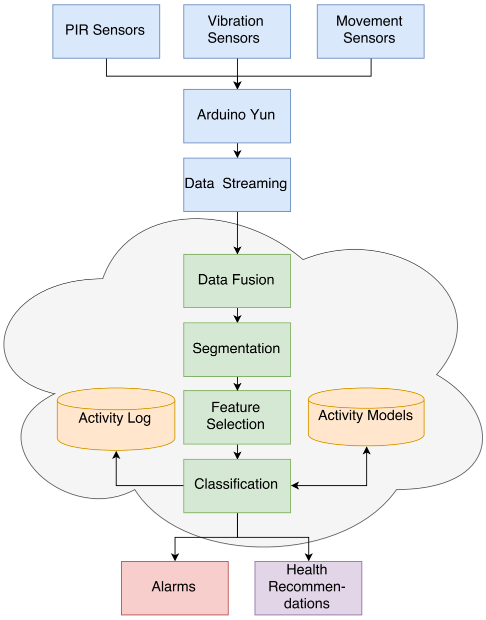

Fig. 1: Logical architecture of the cloud-based privacy preserving system for AAL

As it can be observed in Fig. 1, the classification model generation and usage are both performed in the cloud and the models are kept in cloud storage. Based on the detected activities, a user activity log is kept for further reference, retrospective studies and auditing. Finally, based on the activity classification, the system gives recommendations. If an unhealthy or potentially hazardous activity is detected the system generates an alarm and the designated person is informed about the potential danger. The cloud-based solution is preffered over local processing for several reasons. First, the deployment is simplified and only the bare minimum of hardware resources are deployed locally. In contrast, local processing and classification would complicate the architecture and increase the cost. Second, it simplifes collecting and integrating data from multiple locations, building general models and finding global patterns.

B. Sensors for activity detection

In order to be able to detect generic activities using machine learning, the system needs to be able to process vast amounts of data, which is often complementary and even redundant in order to be able to make reliable predictions. This is accomplished by using multiple sensors that capture information related to the same event from multiple aspects. For that reason we are combining several sensors in a sensor kit, as suggested in [16].

Various sensors are used to detect different atomic activities. Activities that involve human interaction with household objects, such as opening a door, can be accurately performed with simple mechanical sensors that detect contact, motion, or angle and this detection has high level of accuracy. On the other hand, detecting human activity, especially using non-invasive sensors, usually would require using multiple sensors with somewhat lower accuracy [17].

In order to detect a complex action of interest, first the atomic actions that comprise it need to be defined and detected. This study focuses on identifying common actions that are performed in homes, which are not directly detectable by dedicated sensors, but could be detected by a combination of sensors and the context of the activity. Moreover, these atomic actions are composite parts of more complex actions. Given that the sensors are very simple and with limited power, their data is streamed into a central location on the cloud where all further processing is performed.

The ideas of using variety of simple non-intrusive sensors for such tasks was first presented in [16] and this study is continuation of that work. Even though in our project we are using a variety of sensors and sensor kits, in this study we are only presenting the application of only passive infrared (PIR) sensors (Model HC-SR501), as described in [16]. This sensor detects changes in the infrared spectrum, it is highly sensitive and very reliable. Its use is specific in detecting movement of people. We use this sensor in a setup consisting of five sensors positioned at an angle of each other [16]. Despite the many technical limitations of these sensors, they have a key property that the data they collect cannot identify a person, rather only detect a person. Therefore it intrinsically addresses privacy concerns, raised by more advanced sensors such as cameras, microphones, GPS, accelerometers, etc.

C. Classification algorithms

One of the classification algorithms used in our experiments is *logistic regression* [18]. For small datasets it is very simple and fast and provides models that are easily interpretible. *Random Forest* (RF) [19] is an efficient algorithm that creates an ensemble of decision trees by randomly sampling training instances from the dataset and also randomly selecting features from each sample. Similar to RF, the *Extremely Randomized Trees* (ERT) algorithm [20] also generates an ensemble of trees. ERT chooses the split from the attributes randomly, unlike RF where the tree branching is performed by finding the best split from the features on each node. During classification, in both RF and ERT trees vote for the class and the majority class is eventually predicted. Both algorithms provide excellent classification performance and can train models on very large datasets very fast. Both ERT and RF provide feature importance estimates, which is a property used for feature ranking and discarding of low-importance features during the feature selection phase. We have used the feature importance estimates when training an ERT classifier due to its better speed than RF.

Additionally, we have also used the *Support Vector Machines* (SVM) classifier [21] with Gaussian kernel. Even though SVMs are much slower algorithms as the dimensionality of data increases, they are very powerful, especially after parameter tuning [22]. Whenever we used SVMs, the datasets were normalized, so the training dataset will have mean and standard deviation of 0 and 1, respectively.

D. Feature extraction

The raw measurements from sensors usually can detect atomic actions or states, such as: opening a door, flushing the toilet, presence or absence from a room, etc. However, more complex actions depend on the context, which can be captured by recent measurements. Therefore, the data needs to be first segmented in a suitable way and then feature extraction needs to be performed [23]. This study also discusses the window size impact in human activity recognition. Generally, lower sensor frequencies or more complex activities entail longer windows. This is taken into consideration during our experiments by using various window lengths and analyzing the accuracy depending on them. The segmentation into windows, step 1 on Fig. 2, was performed only within a single activity, thus excluding the border intervals when the activity changes from one activity to another.

From all time series, step 2 extracts the following types of features, which have been proven to be effective predictors for activity recognition in Ambient Assisted Living systems [6] and reduction of false alarm in intensive care units [24]:

- *Basic statistics*: minimum, maximum, range, arithmetic mean, harmonic mean, geometric mean, mode, standard deviation, variance, skewness, kurtosis, signal-to-noise ratio, energy, and energy per sample, which results in 14 features per time series.
- *Equal-width histogram* [25] based on the Sturges rule. It results in 5 to 8 features, when the window length varies from 5s (25 measurements) to 20s (100 measurements).
- *Percentile based features*. From one time series, it generates 14 features corresponding to 14 different percentiles [26].
- *Auto-correlation* using the classical auto-correlation and Pearson correlation of the measurements within one sliding window [27], yielding 8 to 10 featuers per time series.
- *Pearson correlations* between pairs of time series, used also in [27]. For 5 time series, this results in 9 features.
- *Linear and quadratic fit coefficients*. There are 2 linear fit and 3 quadratic fit coefficients, yielding 5 features in total per time series [27].

As a result of step 2, depending on the window length 250 to 270 features in total are generated.

Next, using the algorithm proposed proposed in [28], step 3 performs feature importance and drift sensitivity estimation. Next, step 4 performs coarse-grained feature selection with [29], a method based on [28], which tests a set of thresholds which are used to discard features that have low importance or high drift sensitivity. Using it, the system evaluates different feature sets by building classification models using the training dataset and evaluating them with the validation dataset. The test set is not utilized at this stage at all. Thus, only the feature set that results in best classification accuracy is retained. To summarize, the purpose of this step is to significantly reduce the feature set size by discarding features with low importance or high data drift sensitivity.

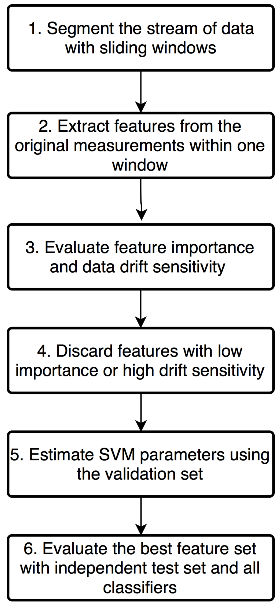

Fig. 2: Feature extraction, selection and classification flow

After the feature set is reduced, step 5 uses the training and validation sets to perform parameter tuning for the SVM. Finally, step 6 evaluates different classifiers by building classification models with the union of the training and validation dataset, and evaluating it using the independent test set.

IV. Experimental setup

Our experiment consisted of one participant performing 5 actions, each of them for 3 minutes, thus obtaining measurements for 15 minutes. A brief description of the actions and one additional state is provided below:

- Walk from one end of the room to the other end,briefly stop and turn around, walk to the other end,briefly stop, turn around and repeat.
- Lay down in the bed, stand up, walk to the corner of the room, turn around briefly stop, walk back to bed and repeat.
- Walk inside of the room, walk towards the desk, sit in the chair, stay still, get up from the chair, walk out of the room and repeat.
- Laying on the bed turn to the side, stay still for few seconds, turn on the back, stay still for few seconds and repeat.
- The person is out of the room.

On Fig. 3 is shown the floor plan and general sensor layout used the experiments. This study uses only the PIR sensor kit, consisted of five PIR sensor, which is ceiling mounted in the center of the room. Even though the other sensor types were installed, in this study they were not used.

The experiment was recorded with video camera only for the purpose of labeling the data manually. During the experiment we used the sensor kit discussed earlier in section III-B and described in more detail in [16]. The sampling rate was set to 5Hz, thereby measuring 5 binary values from 5 PIR

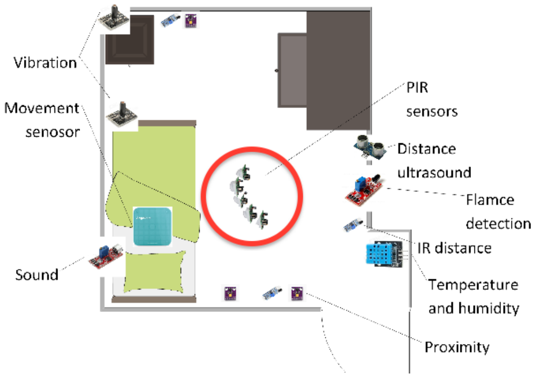

Fig. 3: AAL laboratory floor plan and sensor layout

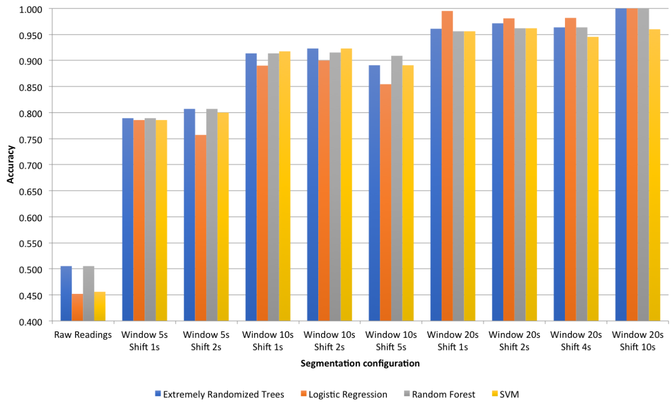

Fig. 4: Accuracy depending on segmentation configuration and classification algorithm on independent test set

sensors every second. As a result, for each action there were $3 \times 60 \times 5 = 900$ records per action. In total for all 5 actions there were 4500 records with 5 binary values each. We divided this dataset in three distinct subsets: for training, validation and testing of the machine learning algorithms. The training set consisted of the first 400 records for each action and the validation set consisted of the next 200 records. The remaining 300 records belonged to the test subset. When performing parameter tuning for SVMs and doing feature selection, the training set was used for building models and the validation set for evaluating their performance. Once this phase completed, the final evaluation was performed only with the best feature set after the feature screening and using the most optimal C and gamma values for the SVM parameters. To make final predictions, the union of the training and validation sets was used to build classification models, while the test set was used for making predictions and the performance evaluation.

Considering size of the data set and the sampling frequency and according to the recommendations in [23], we have decided to use the sliding-window configurations listed in Table I. Additionally, we have performed an experiment when instead of using the sliding windows, we have used the raw readings (i.e. measurements) from the sensors. Depending on the overlapping between consecutive windows, the number of samples in the dataset varied. Using larger overlapping (i.e. smaller shift) yielded more training and test instances.

TABLE I: Sliding window configuration. Gen. feat. is the total number of generated features, and Sel. feat. represents the number of selected features.

Window (s)	Shift (s)	Overlapping (s)	Gen. Feat.	Sel. Feat.
5	1	4	250	29
5	2	3	250	13
10	1	9	260	25
10	2	8	260	16
10	5	5	260	13
20	1	19	280	31
20	2	18	280	29
20	5	15	280	27
20	10	10	280	32

V. Results and Discussion

The accuracy of the different classifiers based on different sliding window configurations (see Table I) are shown on Fig. 4. The first obvious realization is that raw readings provide poor accuracy of up to 50% compared to the approach with sliding windows. This confirms the suspicions that the simple binary PIR sensors are not suitable for creating prediction models for detection of more complex activities.

It can be also observed that when using windows of 5 seconds resulted in accuracy of about 80%. When the window length was increased to 10 seconds, the accuracy has improved and was about 90%. Next, when increasing the window length to 20 seconds, the accuracy further improved to above 95%. In fact, when the shift between adjacent windows was 10s, the accuracy was as high as 100%. However, we reason that this is is due to the reduced number of instances, which could result in over-fitting. To investigate this, in our future experiments more subjects will participate performing activities for longer periods.

Another interesting discovery is that window overlapping did not significantly influence the classification performance, apart from the case of 20s long windows with 10s overlapping, where it yielded almost perfect classification.

Regarding the performance of classifiers, all of them had comparable performance. It is clear indication that the feature extraction and selection process resulted in a small and robust feature set of up to 32 features (see Table I), appropriate for variety of classifiers. Given that ERT, RF and logistic regression do not benefit from parameter tuning, unlike SVM, for this problem we recommend using them. Another reason for that is because they are faster.

The fact that accuracy is increasing for larger window length is an important discovery. It can utilized for design of a system that makes several predictions at the same time. Using shorter windows can result in providing predictions in a real-time like fashion with small delay after an action is being performed. Then as time goes by, the system can make more accurate predictions.

VI. Conclusion and Future Work

In this paper we have discussed the opportunities to design kits of non-intrusive simple sensors that can aid in detecting activities in smart homes. By installing one such sensor kit consisted of five binary PIR sensors, we could monitor and collect data about an experiment in a prototype laboratory. Using simple hardware the data was streamed to a cloud based system, where it was fused. Using a systematic and automated feature extraction and selection process, we could extract robust and reliable features that facilitated building powerful classification models that resulted in accuracy of over 95%. The main weakness of our study is the experimental setup, which we plan to considerably improve in our future work. Namely, we will define scenarios with complex actions, to be performed by multiple participants from different age groups. Using the data from such experiments, more reliable results should be provided and the impact of layout of the rooms and positioning of the sensor kit on the classification performance should be analyzed. Moreover, the scaling implications as the number of users increase need to be also analyzed. It should be also investigated how to system can cope with a real-world situations in which more than one person co-exist within the same environment, and how the system can distinguish between activities of various users in that case. If sufficient accuracy cannot be achieved in such cases, then the use-case of the system can be limited to appropriate environments, such as aging homes where one person lives in one apartment.

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