Challenges in data collection in real-world environments for activity recognition

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***Abstract*—Detecting and recognizing activities of daily living is an important part of ambient assisted living (AAL) systems. This part of the system has the highest impact on the overall system efficiency because it directly provides insights into the user's health state. One of the main challenges that AAL systems are facing are the privacy concerns and the intrusiveness of the sensors that are being deployed. In an ideal scenario, an aged person should be able to continue his or her normal life without noticing that they are being monitored. Another issue for such systems is the data collection. The current approaches usually use data generated in labs and data from end-users users is usually unavailable due to ethical concerns and the inability to deploy them in their living environments. Publications that rely on real-life scenario data are scarce. In this paper, we present the challenges one faces when trying to produce a sound dataset for further analysis and suggest ideas for overcoming them.**

***Index Terms*—ambient assisted living, daily activity recognition, data collection, field conditions**

I. Introduction

Ambient assisted living (AAL) [18] systems have been introduced in the past decades as a response to the aging world population [15]. The problem with the aging population is that with the increased quality of the health-care system, the percentage of the aged population is increasing. With the increasing of the number of aged persons, the health-care system costs are also increasing, and the funding of the health-care system is becoming a very challenging task. AAL could be used to reduce the burden to the health-care providers and caregivers by automating parts of the processes, especially patient monitoring.

The main idea behind AAL is that the aging population needs to have the means to be as independent as possible and to be allowed to live their lives as healthily and happily as possible. One of the main challenges in AAL is the Activities of Daily Living detection by using Ambient Intelligence [14]. The concept of Ambient Intelligence allows employment of the state of the art ICT achievements in order to detect and classify the activities performed within the premises of the living environment that is being monitored. Machine learning methods, and feature and sensor selection processes can be used to make the detection and classification more accurate [21]. The improvements of the machine learning and communications technologies allow the usage of cloud-based solutions [20] towards preserving the privacy of the patients and the data storage and ownership. Machine learning is also used to assist in the development of non-invasive sensors that could also be employed in AAL environments [16] and can later be used for developing classification models [8].

Quite a few examples of proposed AAL architectures and utility subsystems are present in the literature. Although the number of examples where non-invasive sensors are being used is not considerable, there are examples where such sensors are used. Non-invasive sensors are sensors that do not invade the privacy and do not interfere with the daily living of the users. Such sensors can be ambient sensors that are placed in furniture or in buildings and body sensors, such as smart bracelets and watches. Although bracelets and watches do not generally invade the privacy of the users, they are not perceived as fully non-invasive because they are subject to acceptance by the user and the user must wear them all the time. Nevertheless, these sensors are often used for activity recognition tasks and are quite successful [7].

There are examples where 3D sensors and cameras are used for fall detection and activity recognition [9]. Such sensors deliver great results for the recognition of activities of daily living. One of their shortcomings is that they are subject to third-party attacks during the data transfer, which compromises user privacy. They also require greater processing power. Another approach is described in [11], which uses keystrokes to identify users on a computer and identify their usage habits. The approach is non-invasive in nature but can still be abused because it can be correlated with other data from the computer by a third party.

Other approaches also require employing complex algorithms for activity detection and recognition. The signals from the sensors are usually analog and need to be processed in a pipeline. The recognition of the activities is challenging and there are many approaches that assess this matter. For example, in [1] authors propose an ontology-based representation of the activities and by defining rules, an inference engine is able to deduce the location and intention of the user. The approach described in [5] uses accelerators data for activity recognition. Authors have optimized the data processing, so it can run locally on smart-phones, which significantly decreases the security risks. The processing power of the phone, however, would limit the possibility of higher-level activity recognition and personal health-care models for the users. Another approach that uses accelerometers is presented in [4]. Authors achieve very high accuracy for the recognition of the selected activities, however, the user must still wear the wrist sensor to facilitate the activity recognition.

In [17], authors propose a wireless sensor system that is deployed in the living environment and does do not require wearable devices or cameras. The proposed system is tested in a living environment of healthy and unhealthy users and the authors report high accuracy in daily activity recognition. Authors use a device worn by users to log the activities performed in real-time. This approach is suitable for healthy patients and can be used for labeling of data and proposing good models. However, authors do not give details about the practical deployment strategy in any environment. Authors in [19] propose a monitoring platform to ensure a healthy life of aging people. They validate their platform through simulation, which is not always as accurate as real-life tests.

Authors in [3] propose a non-intrusive and low-cost approach that uses only presence sensors and smart switches. The approach is truly non-invasive since a third party can not identify the person that is performing the actions within the living environment. Authors aim to verify user activities.

The approach that we use for deploying a system for ADL recognition based on low-cost and non-intrusive sensors is similar to [3].

Since we are using sensor data and we are deploying sensors connected to a network, there are more things that need to be addressed such as the validity of the sensor data [13] and other challenges, especially when we are entering the era of Internet of Things [10], of which AAL systems are increasingly becoming part of.

Our approach is based on our previous work, as described in [6], where we investigate the initial distribution of sensors in an experimental environment. The main contribution of this work is that we explored the limits of Passive Infrared Sensors (PIR) for simple activity detection and reviewed the challenges that need to be overcome during the deployment of sensors in a nursing home for older adults, and the data collection and processing challenges.

II. Experimental setup

The idea of using non-invasive sensors is not novel. According to [2], the third generation of AAL systems is already being developed where the focus of the development is already shifted towards less intrusive prevention, monitoring and assistance considering user privacy. The main idea behind the third generation AAL systems is the prevention that can be performed by using user-centric models. These models allow the AAL system to develop a user profile that can be used for anomaly detection in the user behavior and when integrated with the health-care provider's data.

In order to obtain a proper sensory placement configuration and a usable model for ADL recognition several requirements need to be fulfilled:

- The privacy of the user must be guaranteed during all stages of deployment and calibration
- No intrusiveness is allowed, the sensors must be environmental and they must be placed on furniture or walls without being too visually invasive
- The data generated from the sensors should be compressible so that less bandwidth is used for the transfer to the servers
- Machine learning approach should be used for sensor placement and calibration of the activity recognition
- The deployment and processing cost should be low

For these points, we have decided to use the Passive Infrared Sensor (PIR). It only detects movement within a certain area and does do not provide any information about the moving person. Another reason for choosing the PIR sensors is that they are widely available, cheap and their prototype production cost is less than 10$, including the casing, and it would cost even less if mass produced.

The main drawback of using non-invasive PIR sensors is the difficulty in their deployment. It is always specific to the floor plan of the place where they need to be installed. This is why we deployed two packages of sensors in a single apartment in a nursing home where an aging person was living.

The deployment of the sensors is shown in Figure 1. Each sensor package consists of 5 PIR sensors. Figure 2 shows the casing. Due to the fact that the PIR sensors cover around 120^o, we were able to cover the whole apartment for movement detection. One of the PIR sensors detects movement below the sensor, another detects movement in the bed, other on the coffee table and the other two, near the window and near the room exit door. The sensors overlap so there are parts of the room where at least two distinct sensors would detect a movement.

The second sensor is placed just outside the corridor of the small apartment so it can detect if a person is exiting or entering the room or the bathroom.

The signal from the sensors is gathered using an Arduino UNO board that is connected to a server for data collection and processing. The signal from the PIR sensor is a binary signal that reads 1 when a movement is detected and 0 when there is no movement. This makes the sensor ideal for detecting movements in parts of the room. The reasoning behind this idea is that if there are different sensors activating at a different time, within a certain time window, we can recognize the activity.

For example, if the person goes to the bathroom from the bed, first the PIR sensor pointed towards the bed will return a 1. Next, the sensor pointing down from the PIR case in the room will also return a 1. Subsequently, the sensors pointing towards the corridor door and finally, the sensor pointing towards the bathroom door will return a 1. Since the activities that are being detected are not very frequent and usually occur slowly, the frequency of gathering sensor data was 5Hz. This would give enough samples to identify movement in certain areas of the room and, at the same time, reduce the collected data volume. Furthermore, since the PIR sensors provide only

Fig. 1. Deployment of sensors in retirement home

Fig. 2. Casing and sensor placement within the casing [6]

1s and 0s, the ten values of 1s and 0s can be further encoded and transferred in a compressed format. Namely, each sensor is represented with only one bit of memory.

III. Acceptance and Ethical Considerations

When performing an experiment in a real-life scenario within the premises of a privately owned apartment or wherever there is a risk of invading someone's privacy, there are always ethical considerations to be taken into account. This is especially true AAL systems [12].

Prior to placing the sensors in the room, we obtained permission from both the manager of the nursing home and the person who lived in the apartment. While discussing the goal of the experiment and the outcomes that were expected, we found the person to be very enthusiastic and cooperative. One of the most important reasons why he accepted to have sensors installed in his room was the fact that they could not actually identify him, that his privacy was guaranteed and that the activities performed would be detected without correlation with who actually performed them. Furthermore, the atomic activities that were selected were not giving away personal information, such as who visited him and who was he having a conversation with since no microphones or cameras were deployed.

IV. Data Obtaining Approaches

Prior to obtaining and labeling the data, the annotation of the actual and target activities was the most challenging. We took two approaches to gather sensor data from the apartment.

The first approach was to have a timesheet maintained by the person. The target activities were:

- going to bed
- going to the coffee table
- eating
- going to the bathroom
- entering the room
- exiting the room

Although the person was very collaborative, the timesheet approach posed two problems:

- Irregular fillings in the form so that very few activities were actually logged in.
- Wrong times of logging. Being an older person who was partially visually impaired proved to be a problem when filling in a timesheet.

After a week of time sheets, we only obtained logs for around 20 to 30 activities, which were too few for the activity recognition problem using these types of sensors. Another possible approach would be to use wrist-bands or cameras, however using cameras was dismissed since it would invade the privacy of the person and we wanted to find a way that would be able to calibrate the system and model the activities without doing it. Wrist-bands or smartwatch were also not usable in the current scenario since they would be invasive in terms that the person would be obligated to wear them all the time while the experiment lasts which contradicts with the requirements.

The second approach was to use the time when the person is not present in the room and do the calibration ourselves. We filmed a total of an hour and 30 minutes using a camera that was synchronized with the sensor server. We were then able to identify the activities from the camera and mark them within the dataset. In this way, we were successful in obtaining a small labeled dataset.

Nonetheless, the dataset is not enough for training a model since there are six distinct activities, each of them 20 seconds long, and pauses of 20 seconds between them. Consequently, there are at most 20-30 samples for each activity, which is usually not enough for training a robust model. Furthermore, the PIR sensor provides 1s only when it detects movement, which needs to be substantial so that the PIR sensor can detect it.

Part of the data sequences is visualized in Figures 3 and 4. Two differently labeled activities are visualized. It is evident

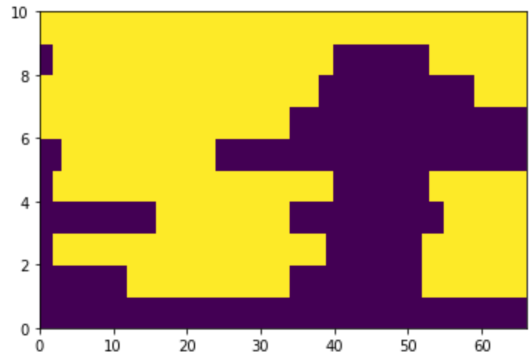

Fig. 3. Visualizations of the sensor values for going to bathroom activity. The Y-axis shows the sensor Id, and X axis is the time.

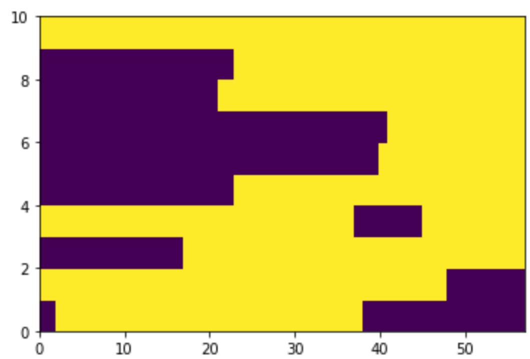

Fig. 4. Visualizations of the sensor values for going to bed activity. The Y-axis shows the sensor Id, and X axis is the time.

that the activities cause different sensors activations within the frame when they are being recorded. Yellow being Ones and Magenta being zeros. Furthermore, some activities last longer than other activities, which raises additional problem when trying to find an optimal sliding window for the analysis.

V. Data processing pipeline

The obtained dataset consists of a time series readings from the deployed 10 PIR sensors. We deployed the sensors in boxes of five. Due to the configuration of the space and the specificity of the activities from the person of the experiment, we were aware that we would not be able to utilize all of the sensors. The sensor pointing towards the window in the room and the sensor pointing towards the wardrobe in the corridor were never activated because there was no movement within their range.

For the feature extraction based on the sensor readings, we applied the framework described in [21], [22]. The framework performs feature extraction in several steps. First, it segments the data using sliding windows with 50% overlapping. Then, from each PIR sensor, multiple statistical measurements are calculated, such as minimum, maximum, mean, standard deviation, skewness, and kurtosis. More complex features were either redundant or non-informative, considering that the time series of a PIR sensor has binary values.

After all of the features are generated, for each feature the framework estimates the *feature importance*. All estimations are performed using a Random Forest classifier with 1000 trees and using its feature importance estimates. In addition to the importance, the framework also calculates the concept distribution drift sensitivity of each feature, as described in [21]. The features that we select for the classification need to have high importance and low drift sensitivity. For this purpose, we perform a grid search with Random Forest to select the optimal combination of features from the calculated set.

With the feature selection, the number of features is reduced to obtain more robust models and to shorten the model building and recognition time. After the feature selection process, using several machine learning algorithms, we generate classification models using the reduced feature sets.

We define the prediction model by the feature subset, classification algorithm, and algorithm parameters. The evaluated classification algorithms include Random Forest, Extremely Randomized Trees, Support Vector Machines (SVM), Nave Bayes, Ada Boost, Logistic regression, and kNN.

VI. Conclusion and future work

Based on the experiments performed within the premises of a real living environment we concluded that designing and deploying a non-invasive AAL system for ADL recognition proves to be a very demanding task.

The requirements given in this experiment came from the fact that a sound ADL recognition system would be easy to deploy and calibrate without the need for a significant burden to the user. Also, the calibration process should be as short as possible and as the recognition process, should do not be intrusive. Despite the sound logic that PIR sensors would be enough to detect certain activities, our machine learning pipeline was not so successful using the small amount of data that we were able to obtain in the short amount of time.

Several ideas came to overcome the problems at hand such as using the analog signal from the sensor in order to recognize activities even when the movement is not significant. This could increase the number of potential activities that can be recognized but at the cost of reducing the ability to compress the signal and also would require increasing the frequency of data collection from the sensors. Increasing the data flow quantity would also increase the processing price which we aimed to be as low as possible. The combination with smart switches or other non-invasive sensors is also possible and would probably increase the recognition quality but will also increase the processing power needed.

Producing a well-labeled dataset for ADL recognition that can be used in a real-world environment is a challenging task that requires overcoming few deployment problems. We treated the experiment from the point of view of having a useful and commercially ready system that one could use outside a laboratory in a real-world environment. Several points need to be addressed in order to achieve this. First, the sensors should be adequate for the activities that we need to detect.

In our case, one of the chosen activities was impossible to detect. Second, the initial training of the system should be done quickly and robustly and enough data should be available for this to work in a real-world environment. For aging people, this could possibly be a challenge since much time would be spent on generating the initial data on which the recognition models could be trained. Asking a person with walking difficulties to repeat tasks is not acceptable and employing people for the same tasks would significantly increase the deployment price. Another drawback of this non-invasive system is that it is unable to distinguish if the movements are performed by the person of interest or another person is present in the room.

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