Towards Application of Non-Invasive Environmental Sensors for Risks and Activity Detection

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***Abstract*—One of the main goals of Ambient Assisted Living (AAL) is to provide supportive environment for the elderly or disabled. Such environments are not feasible without correctly identifying states and activities of the persons receiving the care. They rely on the interaction and processing of data originating from many components and objects in the surrounding. In order to collect the data, various sensors are used to monitor the environment, as well as the person's health parameters. One of the main concerns in AAL is preservation of user's privacy. In this paper we address that by proposing a non-intrusive approach for data collection and identification of daily activity and risks. We describe the wiring of such system based on cheap non-intrusive sensors, deployment in a real environment, the protocols for data fusion and processing, and explain how machine learning could be employed for detecting risks and activities. The main contribution of this paper is development of non-intrusive sensor kits that can be easily deployed in real-life environments and are capable of collecting data that can reliable detect activities and risk.**

Keywords*—Sensors, Ambient Assisted Living, Machine Learning, Data Fusion, Time Series Analysis, Pervasive Computing

I. Introduction

The aging of the population in many industrialized nations has become a challenge for the societies. Ambient Assisted Living (AAL) is a research field that strives to address the problems associated with aging and by using technology, provide means for the elderly to remain more independent and assist the human care providers in daily care. Current state of the research of AAL can be summarized as very broad and having many related fields. In this paper we focus on collecting sensory data about the environment and the person involved. While there are multiple approaches and solutions in the recent literature for AAL, when it comes to sensing the environment many of the proposed solutions are either very intrusive or very complicated to implement and require that every object, like household appliances or even the furniture, to be part of the ecosystem [1]. With the rise of the internet of things (IoT) we can expect that many devices will be connected and provide interfaces for monitoring and control. However, providing sustainable AAL solution means that it should be applicable in an average home and not just in labs or specialized institutions such as hospices.

This paper will approach detection of risks and activities of daily living (ADL) focusing on non-invasive sensors which preserve the privacy of monitored individuals, do not interfere with their normal routines and do not require wearing of tags.

This paper proposes the use of generic sensors in the environment combined in sensor kits and using machine learning (ML) to enable detection of activities that are not directly monitored. We will also identify limits and downsides of this approach.

In the next section we describe the related work in the literature. In section III our approach in data collection is described including scenarios for activity detection. Data processing and activity detection using machine learning is described in section IV. Section V concludes the paper.

II. Related work

Activity detection is a research field that is not limited to AAL. For example, recently it has been demonstrated that it can be used for monitoring of activities of firefighters, such as climbing ladder, running, throwing hose, carrying hammer in order to detect risks and improve safety and effectiveness [2].

Activity detection has also been a topic with increased focus within AAL research. In [3] the authors present an overview of the research to identify examples of sensor data fusion techniques that can be applied to the sensors available in mobile devices aiming to identify activities of daily living. A scenario using kinematic sensor to detect activity of the elderly is described in [4]. The authors in this paper showed that a single sensor can be effective in detecting multiple states and activities of the elderly such as turning on the bed, transferring in and out of bed, standing, and walking. A wrist worn sensor was used in [5] to detect activities in AAL scenario. The system did well in detecting sleeping, sweeping, walking and was less successful in detecting dressing or undressing.

As we can notice from the aforementioned examples, most of activity detection is focused using mobile and wearable sensors. While wearable sensors have multiple advantages and have shown promising results more research is needed with non-intrusive approach, specially one that will be easy to deploy and will be affordable.

Research was also done using environmental sensors. One such case is [6] where sensors were used to detect activities that have patterns. In this system temporal information are vital part to detect repetitive activities and use that information to proactively adapt the environment to the residents.

Fall detection is one of the scenario that is researched very often in the literature. Various systems using environmental sensors have been proposed such as using acoustic detectors as done in [7], [8], and [9], or a floor vibration sensor as used in [10]. Video based fall detection is presented in [11].

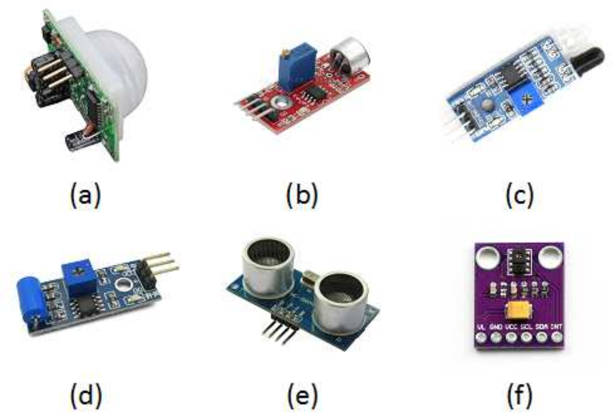

Fig. 1. Sensors: (a) PIR, (b) microphone, (c) IR obstacle, (d) vibration (e) ultrasound distance, (f) proximity

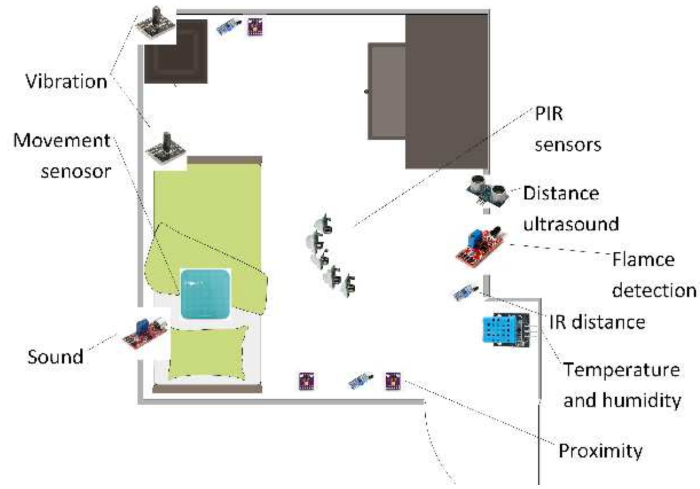

Fig. 2. AAL laboratory floor plan and sensor layout

Andoh et al. propose health monitoring system using mattress that monitors body movement and breathing using microphone based pressure sensor. Using fuzzy logic categorization they detect the different stages of sleep [12].

In AAL systems the quality of service has to be at a very high level, guarantying reliable and accurate performance at a reasonable price while preserving user's privacy. Authors in [13] propose modular architecture that gives guidelines how these challenges can be addressed. Keeping that in mind, using non-intrusive sensors will mitigate privacy concerns while also needing considerably lower bandwidth (e.g. compared to cameras), which in turns can help in the reliability of the system.

III. Sensors and Experimental Setup

In order to develop a reliable sensor based system with capacity to detect generic activities using machine learning, we need to make sure that the system has enough complementary and even redundant data. This will be accomplished by using multiple sensors that will sense the same event from multiple aspects. Among the sensors that might be used, shown in Fig. 1 are the PIR (Passive Infrared) sensor to detect human motion, distance sensors to detect presence of objects and spatial location, microphones to triangulate source of sound, vibration sensors to detect disturbance of furniture and other sensors. The hypothesis that will be tested in this research is that the combined input of multiple non-intrusive sensors can detect events in the environment in lieu of dedicated sensors.

In order to illustrate the proposed concept, let us consider the case when a person gets out of bed. There is a possibility of using RFID and proximity sensors, which will require the person to always wear a tag, something that many people might find intrusive, inconvenient, unpleasant or cumbersome. We can also create a smart bed to detect when it is being occupied, but such investment is unlikely to be made by most elderly people and it will only detect events related to the use of the bed. However, we hypothesize that the combined input from multiple environment sensors achieve the same goal with the same or even better performance in a non-intrusive way. This hypothesis heavily relies on correctly labeling the activities while collecting data, so machine learning based models can be properly trained. Manual labeling of data is a problem of its own, therefore our architecture takes this into account by using sensors that will be used for tagging the data. The goal of the tagging is two-fold: having correctly labeled data, and having a golden standard for evaluation of the performance of the system.

Aside from daily activities, the proposed system can be used to detect risks and life threatening events. In the literature one of the most used scenario is fall detection. Most often fall detection is done by using wearable sensors, smart-phones or by video recognition [14], [15]. However, the ability to use these sensors in private places such as the bathroom is limited due to privacy concerns. The sensors mentioned in this paper are not intrusive and can be used to detect fall events even in bathrooms.

For the purpose of this research we are using ALL laboratory equipped with sensors. Its floor plan and sensor layout is shown in Fig 2.

In the following subsections we present the sensor layout, as well as a scenario for physical activity of opening a room door and risk detection by monitoring vital signs during sleep.

A. *Sensor layout and data gathering*

In this subsection we describe the sensor layout and methodology for optimal placement.

For optimal experimental results we will use wired connected sensors which will be directly connected to the microcontroller. In the real world scenario sensors in proximity can be grouped and connected to XBee or other wireless module to avoid the complications with installations of wires in which case it is essential to establish time synchronization between the modules as temporal differences might change the effectiveness of the ML event detection.

Fig. 3 shows a simplified schematics for the sensor connectivity. All sensors can share the same V_{cc} and Gnd connections or they can be powered in groups. For the sensors that require trigger signal such as the ultrasound range sensor we can use

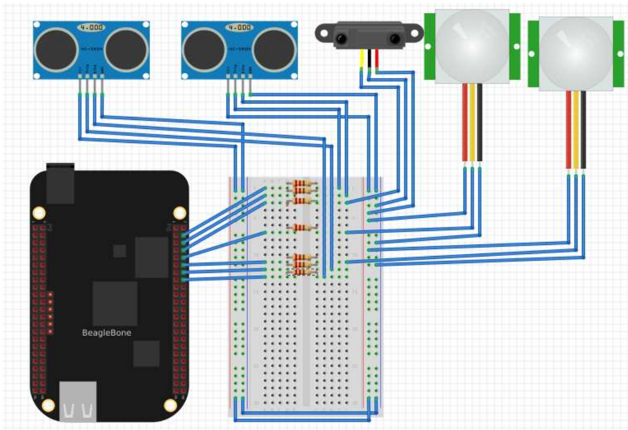

Fig. 3. Simplified schematic representation

one connection to trigger multiple sensors and for sensors that detect change such as PIR sensors we only need receiving GPIO pin. The beaglebone black micro-controller has 64 digital GPIO ports which is sufficient for our experiment. However additional connectivity can be done using I2C and/or multiplexer circuitry. The processing power of the controller is sufficient even for large number of sensors.

We should note that the type of sensor and its locations play important role in the system. For example, a PIR sensor is not precise and can detect any motion in its range of sight as a binary state (presence or absence of motion). On the other hand, the proximity sensors can detect a presence of an object with resolution of up to 16 bit, albeit with limited range. With this in mind, they are complementary and combinations of both type of sensors can alleviate their independent drawbacks.

In order to establish optimal location for a given event detection we will use the following methodology: we detect the performance of ML; then we select a random sensor or sensor group and place the sensor in a different location and simulate the same event, we repeat with few locations and select the optimal placement for the sensor. This process is repeated for each sensor.

ML detect event
for S in Sensors **do**
  for L_s in Locations for S **do**
    ML detect event
    Evaluate Contribution of S in L
  end for
  Select best L for S
end for

Algorithm 1: Optimal sensor placement algorithm

In the lab environment the same can be done by placing multiple sensors of the same type in various locations and running the ML algorithm by removing data from one sensor. The sensor with the least influence on the learning algorithm can be removed and the same process repeated until we are left only with the number of sensors so that if we remove additional sensor the error rate will increase by more than 3% of the entire system.

We should note that this placement is event type specific

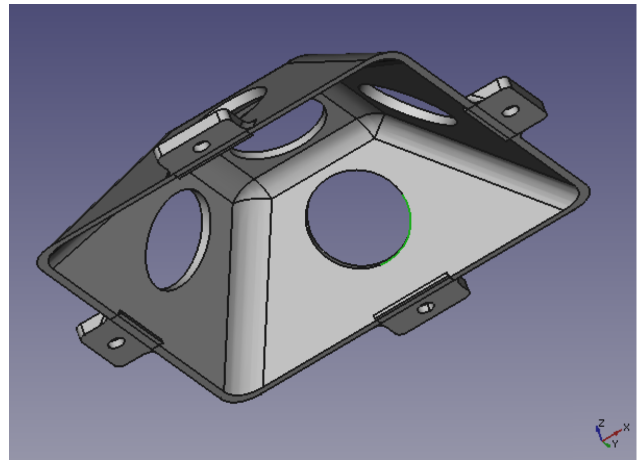

Fig. 4. PIR sensor case in FreeCAD

but the same methodology can be applied by simulating event detection for multiple events.

Another consideration is the relative positioning of groups of sensors. In order to ensure that the experiment can be replicated, we create cases for sensors that need to be grouped. This can be done either for group of same type of sensor or mixed types. Fig. 4 shows the CAD drawing for a case for positioning of 5 PIR sensors. There is one sensor pointing down and 4 sensors placed on 4 sides each at 45° angle relative to the bottom sensor forming a cut pyramid shape. A 3D printed cases device with PIR sensors is shown in Fig. 5. Placing sensors in a case ensures the relative position and angle of the sensors is known and can be reproduced. The position and shape of the case is determined by the size of the sensors and the angle and range of sensitivity. All sensors are glued to the case to minimize chance of displacement.

The use of the 3D printed sensor cases has additional advantages of low price and portability. The goal of this research includes evaluation of the optimal design for sensor cases to maximize the effectiveness of the sensors by finding the optimal relative positioning. The design in fig. 4 and the manufactured product in fig. 5 and fig. 6 show one version for PIR sensors. The resulted design will be used to develop open source CAD device for inexpensive and easily reproducible cases using 3D printers. This cases can be used to create sensor kits that will have standard interface for interconnection with the micro-controllers and will be more easy to deploy in various environments.

B. Detection of activity: opening door

In this subsection, we consider the event of opening a door (e.g. from the bathroom) that can be monitored using environmental sensors. Monitoring how often an elderly person goes to the bathroom is important and changes in pattern can be sometimes symptoms of interest for the care providers. The position of the door can easily be monitored using simple sensors attached to the door, but this will give us information about the state of the door and not always for the activity of the person. For example, the person might open the door, change his/her mind and walk back, so relying on only the state of

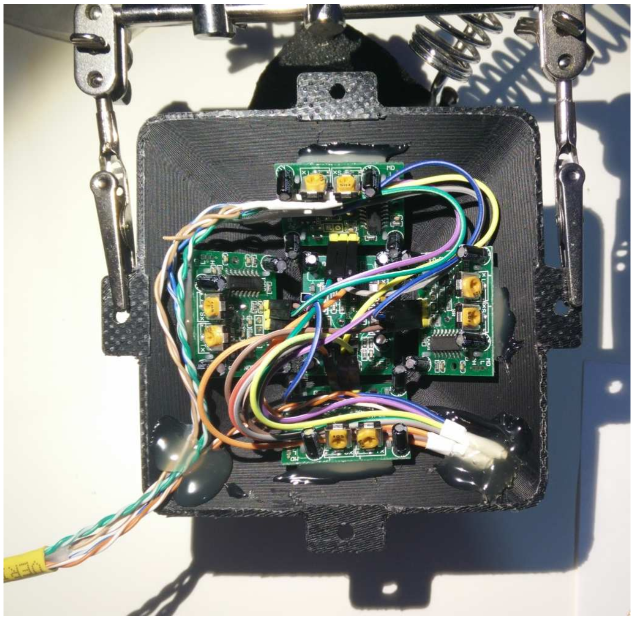

Fig. 5. PIR senor case bottom view

Fig. 6. Installed PIR sensor

the door might sometimes lead to a wrong assumption that the person has entered the bathroom.

Our hypothesis for this experiment is that the sensors from the environment shown in Fig. 1 despite individually being insufficient to make meaningful detection, jointly can detect multiple events.

In order to gather precisely labeled data for the machine learning algorithm we will use a magnetic sensor to detect if the door is open or closed, this sensor will be attached to the same micro-controller as all other environmental sensors to enable precise time stamps. Additional scenarios can include human monitoring and labeling the different events that involve changes in the position of the door such as going through the door or opening the door without entering or leaving the room. To detect events when a person walks through the door which

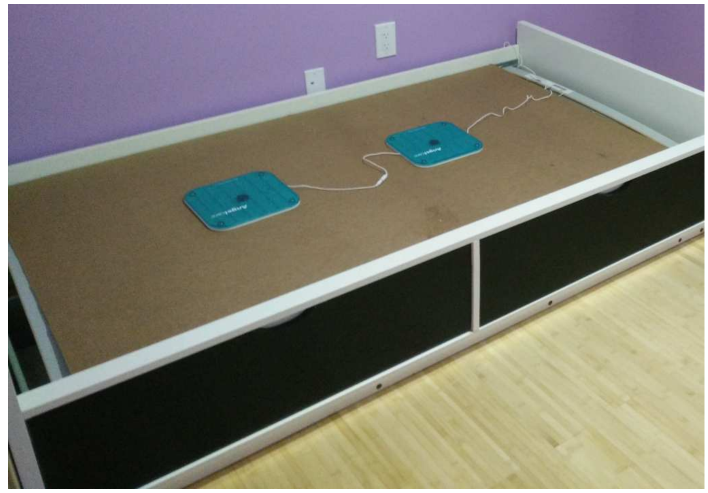

Fig. 7. Movement detection sensors under the mattress

was left open we can use light sensor to detect when person or object goes through.

C. Risk detection: vital signs during sleep

There can be many potential risks to which elderly people are exposed daily in their homes: falling [9], scalding of skin from hot water [16], risks from gas leakage, carbon monoxide, fire and flooding from forgetting to turn off appliances and vents, etc. As most of these scenarios are not appropriate for the proposed setup, and dedicated sensors were already proposed in the literature, we choose the topic of vital signs monitoring. Monitoring vital signs is an established standard in hospital environments, but using such equipment in the home is expensive, cumbersome and intrusive.

Andoh et al. in [12] have shown that sensors in the mattress can be used to estimate sleep stages. By using sensor fusion we propose to detect a presence of a person and vital sign monitoring while the person is in the bed. This data can further be using to detect change is sleep patterns of the elderly occupant.

In order to provide non-intrusive vital signs monitoring we propose using combination of environmental sensors that can detect movement of the person while laying in bed or sleeping and additionally a use of movement sensor which relies on small changes in pressure and is placed under the mattress which is shown in Fig. 7. An alarm will be raised if the system identifies that the person is occupying the bed but the movement sensor doesn't detect changes. Environmental sensors are used to filter false positives. An optional pressure sensor can be used to detect actual presence of a person.

In addition to vital sign monitor such a system can also be used for fall from the bed detection.

D. Experimental setup

In order to provide visualization of the proposed setup we conducted an experiment using the case shown installed on a ceiling in Fig. 6. We have conducted a 15 minute experiment separated in three minute sections. The first four sections represent different physical activities in the room that repeat

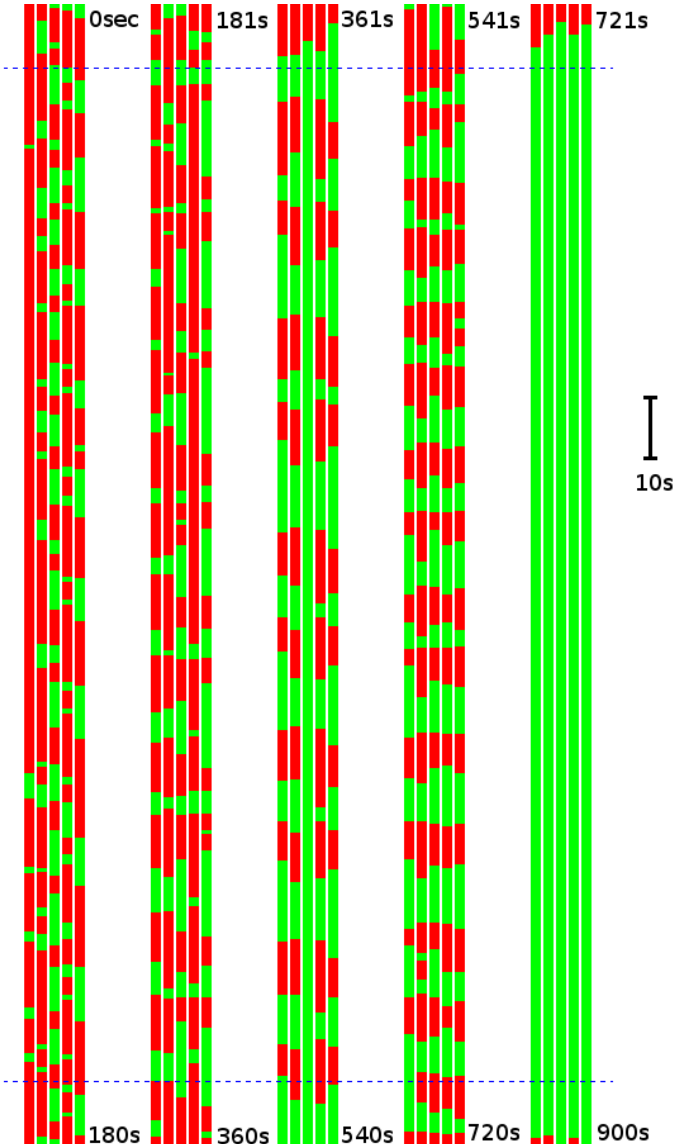

Fig. 8. Visualization of sensor readouts

multiple times and the fifth one is a period of 3 minutes where the person was out of the room. These 5 sections are shown in Fig. 8. The samples above the upper and below the lower dotted (blue) lines can be discarded as they might represent when the person was switching from one activity to the other. Each of the five columns represent an interval of three minutes and each strip within the column is one of the five sensors where red (dark) is detected motion of a person and green (grey) is absence of motion for the given sensor. A line representing an interval of 10 second is represented on the right hand side to show the scale of the activity.

A brief description of the four activities is as follows:

1) 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.
2) Lay down in the bed, stand up, walk to the corner of the room, turn around briefly stop, walk back to bed and repeat
3) 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.
4) Laying on the bed turn to the side, stay still for few seconds, turn on the back, stay still for few seconds and repeat

From this visual representation we can notice the distinct patterns and the difference between the activities. We expect that sensor fusion using bigger number and variety of sensors will enable better feature representation.

IV. Feature Engineering and Machine Learning

Acquiring the data from the sensors and the sensor configuration is one of the tasks that need to be accomplished in order to have a reliable application. The most time consuming and difficult task is the selection of the most informative features from the acquired data as well as the training of the machine learning model that will be able to recognize different activities and states in the environment. Different people tend to perform same things in different ways therefore some physical activity classification needs to be performed with respect to subject identification [2]. The same events could be dramatically differently represented depending of the placement of the sensors and the layout of the area. Establishing deterministic rules based on the temporal sensor readings in relation to the activity is difficult, if not impossible. On the other hand, multivariate analysis of such sensory data is more suitable for feature extraction and consequently machine learning algorithms. Various feature extraction methods from multiple time series based on calculating statistics, histograms, correlations, percentiles, and time series domain parameters have been proven to be effective in activity and posture classification of firefighters [17, 18, 19]. Our goal is to further rank the sensors based on the informativeness of the features extracted from their readings. This will help in determining which sensor types are important for which scenario and will provide feedback how to better set up the experiment in a next iteration. The iterative approach would help in improving the detection by being able to add new sensors, relocate them or remove obsolete ones.

In order to correctly label the activities of interest and establish the golden standard needed for the supervised machine learning algorithms, we will set up additional sensors (magnet and contact sensors) on and around the door. These sensors will also be used during the validation phase. Eventually in a real-life deployment when the performance of the system is guaranteed to be sufficient, they can be omitted.

Fusion of data originating from sensors with different sampling rates is challenging and requires proper clock synchronization and time alignment. The representation must consider the assumption that time series data is not always aligned properly [20], that it is noisy and that it should comply to the constraints of time and space for its processing. By choosing variety of features, the feature engineering algorithms will be able to produce robust features for any given dataset. Filtering noise in sensory data can be performed in time domain by moving averages or in frequency domain by low-pass and high-pass filters [21]. The generated features should also be invariant to many transformations of the time series data, such as amplitude or time shifting, uniform amplification, additive noise, time scaling, etc [22].

Support Vector Machines [23] with Gaussian kernel have been successfully used for classification in various domains, but require significant effort for parameter tuning. On the other hand, Random Forest (RF) [24] are fast, robust, do not require parameter tuning and also provide feature importance estimations. Likewise, Extremely Randomized Trees (ERT) [25] produce similar models in terms of predictive performance, but they are usually simpler which results in shorter training and testing time. Depending on the feature size and volume of data, the appropriate algorithm will be used.

With the increased processing power of GPUs, deep learning approaches that significantly increase the recognition rate of machine learning models have been introduced. One such deep learning approach is proposed in [26] for the task of activity recognition based on time series data from multiple wearable sensors. The deep learning approaches allow features to be generated by the learning algorithm and not manually engineered by experts. They also perform the feature selection automatically and in the end perform the classification task. However, to build a successful model, deep architectures need a lot of data and they are not suitable for problems where there is not enough data available.

A more suitable method for smaller data-sets could be a fuzzy logic based classification of activities. One such approach reported in [27] gives promising results for recognizing regular and steady activities. In order to successfully recognize more ambiguous activities one might consider using Type 2 Fuzzy logic (T2FL) approach that was successfully used for clustering, classification and pattern recognition [28]. T2FL based classifiers need an expert knowledge and manual parameter tuning to perform the classification task. These types of classifiers are especially good under greater data uncertainty and noisy data. Fuzzy classifiers also improve the results of classification when used in combination with other types of classifiers.

The lack of 'one fits all' approaches in machine learning would require thorough experimentation with the data obtained from the sensors. Based on the data an adequate model for action recognition can be selected and then verified with continuous monitoring of the application performance.

V. Conclusion and future work

Ambient assisted living is receiving an ever increasing attention by scientific communities and there are already quite a few approaches described in the literature. Most of the approaches, however, are using types of sensors that are to some extent invasive. Some of the systems require the users to wear electronic devices or to be observed by a camera throughout their daily life.

In this paper we proposed a system that uses noninvasive sensors that would be placed in the users homes and would provide information about users activities. We provided methodology to study optimal sensor placement and to combine multiple sensors into sensor kits. These sensor kits would be placed in such way that they would acquire the data without interfering with the every day life of the user. The specific configuration of the sensors would allow the detection of activities and alert if a hazardous activity has been performed.

To perform the detection and recognition of activities, the obtained data from the sensors will be processed and a model will be build using a combination of feature selection process and machine learning algorithms. Based on the data quantity and distribution, the adequate features from the sensor data and the adequate machine learning approach will be selected for the application.

In the future we plan to design more cases to host various sensors. Such sensor kits will be tested in multiple environments such as homes of elderly people and hospices. Further, we plan to verify the ability of the sensors to acquire enough data so that a reliable machine learning based model could be trained and used for activity recognition using noninvasive sensors. The configuration of the sensors would allow the labeling of the data to be performed in a semi autonomous way and the labeling errors will be minimal due to the sensor redundancy. This would allow us to build accurate models for the users behavior and make the system reliable especially for detecting hazardous situations in the living environment.

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