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Tracking a Person's Behaviour in a Smart House

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Abstract. This paper proposes to use machine learning techniques with ultrasonic sensors to predict the behavior and status of a person when they live solely inside their house. The proposed system is tested on a single room. A grid of ultrasonic sensors is placed in the ceiling of a room to monitor the position and the status of a person (standing, sitting, lying down). The sensors readings are wirelessly communicated through a microcontroller to a cloud. An intelligent system will read the sensors values from the cloud and analyses them using machine learning algorithms to predict the person behavior and status and decide whether it is a normal situation or abnormal. If an abnormal situation is concluded, then an alert will be risen on a dashboard, where a care giver can take an immediate action. The proposed system managed to give results with accuracy exceeding 90%. Results out of this project will help people with supported needed, for example elderly people, to live their life as independent as possible, without too much interference from the caregivers. This will also free the care givers and allows them to monitors more units at the same time.

Keywords: Smart home, people with supported needs, Behavior tracking, Ultrasonic sensors, Machine learning.

1 Introduction

Everyone has the right to live safely and independently in the environment around them. Especially people with supported needs require to feel this independency inside their home, and that they are not continuously monitored by care givers. The advance of Internet of Thing and machine learning is pushing toward smarter homes. Houses can be safer and more comfortable, hazards and risks can be detected and reported, and occupants and caregivers can utilize their time more efficiently.

The aim of the project proposed here is to enable people with supported needs to live their lives well and independently, with least amount of intervention from the caregivers, by creating a smart home using non-intrusive sensors. The proposed system will satisfy the following criteria: Being aware of people's behavior, and track and trace them in the house. Notify caregivers when the occupant needs help or do some actions that might hurt them. Identify factors that caused some hazardous actions to occur. The assumed scenario is that there is only one permanent occupant for a single house, plus a caregiver who can intervene occasionally.

Different types of sensors (e.g. water flow, electricity flow, ultrasonic, pressure) can be used and connected to a number of Microcontrollers to help with the prediction [11]. At this stage of the project we only focus on ultrasonic sensors. All data collected from the microcontrollers will be sent wirelessly to a gateway in the house, which will send the data through a cloud to a main server for processing. The server will use data mining techniques to analyze the data to track and trace the occupant, and distinguish between normal and abnormal behaviors. This process will lead to identify situations that need attention, and predict factors that contribute to hazardous issues. The analyzed data will be visualized onto an online dashboard, enabling caregivers to monitor the current situation and to receive alerts from the system, no matter where they are, for any case that needs attention.

The main challenge of the proposed system is to preserve the privacy of the house occupants. For that no video or audio monitoring is permitted. In general, Occupants should not feel that they are monitored, for that all sensors should be seamlessly integrated and blended to normal household items. Research showed that if house occupants knew that they were monitored, their behavior would change. This is called Hawthorne effect [1][2]. Another challenge is that the system should be able to distinguish among different people in the house, by distinguishing among their behaviors. The main behavior belongs to the occupant of the house, and any other behavior deviating from this main behavior will belong to someone else, could be the caregiver. Machine learning techniques will be used to make about the behavior.

In this paper we create a grid of ultrasonic sensors in the ceiling of a room. Each sensor covers a spot in the room to indicate the height of the occupant. All sensors collectively should track the movement of the occupant, and through the connected micro controller, the data is sent to a central unit for processing and decision making. The ultrasonic sensor that we propose to use for indoor environment is HRLV-MaxSonar-EZ0 that can detect objects between 30 cm to 5 meters.

In the below sections we provide a review of previous research about smart homes for people that need support. Then we concentrate on using ultrasonic sensors to track people in the smart environment, and the decision making process using machine learning techniques. Section 3 describes the system architecture proposed here and the discussion about the results. Finally, the conclusion is in section 4.

2 Smart Homes for People of Supported Needs

Many projects were investigating the usage of IoT and different types of sensors to create smart homes to suit certain requirements. [3] tries to setup a security alarm system for elderly that involves cameras to sense the motion if there is any abnormality, where all data are stored locally for future analysis. The project in [4] is trying to create a smart home for elderly people to live an independent life, which involves camera for facial recognition and PIR (Passive Infrared) sensors for motion detection. In [5], in addition of monitoring the subject's movement using cameras and infrared sensors, they also introduce different sensors, such as pressure sensor mats, stove temperature sensors, switches on doors, and bed sensor, to predict the normal and abnormal activities

of the subject under observation. [6] proposes a smart location tracking using an array of pressure sensors under the floor tiles. The size of the tile is 60×60 cm and each is equipped with 4 pressure sensors on the corners. In [7] a wearable smart sensors are used to detect the fall of a person and distinguish it from the normal activities. Some of the sensors used in their system are accelerometer and chardiotachometer to estimate the impact of the fall.

2.1 Ultrasonic Sensors in Smart Homes

Ultrasonic sensors detect how far objects are from the current point by sending ultrasonic waves toward the objects and measure the time of the returned wave to estimate the distance. Ultrasonic sensors are used in varieties of applications including motion detection, robotics, navigation systems and people detection.

In smart homes, ultrasonic sensors are used either as part of their intelligent monitoring system, or as a standalone monitoring system. Ultrasonic sensors can be mounted on ceiling and/or wall [8]. [9] claims to give an accurate 3D tracking of human activities in a living area using mathematical models to predict the position. Their proposed system uses more than 300 ultrasonic sensors in $3.5 \times 3.5 \times 2.7$ m room, which makes it very expensive and it impractical to monitor people without noticing. In [4] ultrasonic sensors are used to predict how full the trash bin is, as part of the house intelligent system. In [10], a 6×6 ultrasonic grid is installed on the ceiling of approximately 4×4 room to monitor the movement of a child as a child-mother distance and child-stranger distance. Kalman filter is used to track the direction of the movement of the child taking into consideration the last two readings from the sensors.

The sensitivity of the ultrasonic sensors is affected by many factors such as Temperature and high noise [6]. For the work presented here, the room temperature is assumed to be moderate and there is no high noise situation.

2.2 Mining Sensors Data

The history of all the events captured by the sensors at a particular time at a specific location can be used to discover activities, abnormal behavior and to predict the next actions that the resident intent to do [11]. In the following section, we will describe some research that has been done in this area.

Given a raw sensor events tagged with a date and time, [12] applies a priory algorithm [13] to get the most frequently occurring sequences of events that happened in a house. It then identifies the temporal relations between two events as defined in [14]: before, contains, overlaps, meets, starts, started-by, finishes, finished-by and equal relations. The probability of an event A occurs given that we have observed the occurrence of event B is calculated by the total number of times A has any temporal relations with B divided by the total number of times event B occurred. [12] uses the probability theory to calculate the likelihood of event A occurring based on every event that has occurred on the day until that point in time. It also calculates the mean and standard deviations of event A occurred throughout the resident's history. An event is considered

abnormal if the likelihood of that event is close to 0 and its frequency is greater than mean + 2 standard deviations.

They then evaluated their algorithm on a real and synthetic dataset. In the synthetic data, all of the expected anomalies are detected and no false positives are reported. In the real data, no anomalies are reported because it does not contain anomalous event. Unfortunately, we do not really know how well their algorithm performed since they do not explain what anomalous event they have introduced to the synthetic dataset or how did they generate the events in the real and synthetic datasets. Furthermore, from the snippets of their raw sensor events, it seems that they have placed the sensors to some objects in the room.

Many researchers have developed Hidden Markov Model (HMM) to detect anomalous behavior observed in a day using different set of features such as the tempo and timing of the events [15], and the analysis of the resident’s walking trajectories [16]. Given those features and a sequence of events observed so far, the model has to first predict what are all the possible next events. If the next observed event is not in the list of possible events, the event will be marked as abnormal. Because state duration is not explicitly modeled, [17] found that those models fail to detect abnormal behavior caused by a person performing an activity longer or shorter than usual.

Although [15] and [16] models can accurately predict anomalous behavior caused by a resident performing an activity in the order that is different than what was previously observed, they cannot distinguish which activity sequence is abnormal when the order of activities is identical but the duration of one or more activities vary. Hence, [17] have developed a HMM where the state duration is included as a state variable and they called it ESD-HMM.

They then evaluated their ESD-HMM model on a single person performing the following activities in a kitchen in any order they want: preparing cereal, making toast, preparing dinner, cooking dinner, and cooking a bacon and eggs breakfast. The discrete observations are stove, bench, sink, fridge and door. Undefined is used for all other observations. Those activities are chosen because it highlights the fact that a resident might visited the same areas in the room to perform two different types of activities. For instance, to prepare cereal and toast, the sequence is [door, fridge, bench, sink, bench, fridge, door]. We can only distinguish them by looking at the time spent at kitchen’s bench—it takes longer to prepare a toast than a cereal. Their evaluation found that ESD-HMM can predict a person’s activity with 100% accuracy while HMM can only obtain 81.43% accuracy. [17] also evaluated how both models can detect anomalous behavior given 24 normal sequence of observations but the activity’s duration is either shorter or longer than the normal ones. They found that ESD-HMM can reliably distinguish normal and abnormal sequence, better than the HMM model.

[18] creates a Relational Markov Networks model to accurately predict the location of a person based on: (a) temporal information such as time of the day and duration; (b) geographic evidence such as the types of business and whether they are near a commonly visited place like restaurant or store; (c) sequential information on which activities usually followed by a certain activity and how often those activities occurred while the user is at the same place; and (d) context information such as the number of different homes and workplaces the user has.

They have tested their model and basic HMM on 2 datasets: (1) location traces of a single person over period of four months and (2) location traces of five people over period of a week. They found that their Relational Markov Networks achieved 7% error rate on the first dataset and 18% error rate on the second dataset. Their model accuracy is improved when they trained their model based on the information from more subjects. The model created using basic HMM performed worse by 10% than the Relational Markov Networks on both datasets. Although this model was designed to identify a person's outdoor location, the authors suggested that it can also be used to estimate the person's indoor location and activities, and should perform better than the generative HMM.

From all the above, we can see that the essential features for accurately predicting an abnormal behavior are the sensor values, temporal information such as time, duration, tempo, trajectories, and the location where the event takes place. Through those features, we can not only track a person's location but also identify their activities and determining whether that activity is abnormal.

3 Proposed System Architecture

The system architecture is proposed as a mesh of ultrasonic sensors on the smart house ceiling. Sensors are wired to small microcontroller boards enabled with WiFi. The proposed system uses Arduino ESP32 microcontrollers for this purpose. Such devices send the data from the sensor grid to a database on a server over the network. A machine learning system is used to look for events or patterns on the data to describe different behaviors of the occupant in the house. There is a web interface frontend installed on the server publicly available, for a caregiver to access and monitor. Figure 1 show the general architecture of the proposed system.

Data from sensors can give static and dynamic information from the environment. The first one is when a sensor is activated due to the event on the presence of a person, and their location can be computed; the later refers to patterns, a series of these events measured through time, which define behavior patterns, such as walking, running, or sitting. Behavior patterns will later be classified as normal, abnormal, no activity, sitting, standing, laying, etc.

Mosquitto, an open-source local MQTT server (usually called an MQTT broker), is installed and setup on the server, and used to route the sensors' readings from the Arduino ESP32 microcontrollers (MQTT Clients) to a database. Later, Weka is used for the machine learning training to decide on the best model to make decision about the behaviors. A web-based dashboard is also created on the server to show the activities of the house occupant, and can be accessed by the caregiver to monitor these activities.

Fig. 1. General architecture of the proposed system. The readings from the ultrasonic sensors are directed through the microcontrollers to the server for processing.

MB1003 EZ0 ultrasonic sensors are placed on the ceiling with 60 cm apart from each other on a grid, as they were tested to have a 30 cm radius reach. [19] provides a detailed study for optimum distribution of ultrasonic sensors in smart homes, their locations, their angles and the distances among them. Readings come from the sensor 10-bit ADC convertor. Analog voltage bits (0 to 1023) can be read directly and give a proportional distance from the sensor to an object in mm. Each bit corresponds to 5mm.

In this prototype, as shown in figure 2, we only used 9 sensors to cover the area of interest, which is the grey area shown in figure 2, where most of the activities of the occupant happen. The 9 sensors are connected to the microcontroller, which is then connected to the LAN using its WiFi adapter. The microcontroller sets up a session with the broker using MQTT protocol and publishes the signals periodically to the broker. Signals are concatenated and published on an MQTT topic.

The analog inputs on the microcontroller are used with sampling rate of 1 sample/s. An MQTT client, coded with Python, is also running on the same server where the broker sits. It sets up a session with the broker, subscribes to the topic where sensor signals are published, and stores them on a SQLite3 database on the server itself. Topic payload is a string containing the sensor values concatenated in the following format:

1299:976:1296:1328:976:1166:384:912:1313

These values represent an estimation of the distance from a sensor to an object, which are functions to the analog it values.

Once the Client receives a new message on the topic, a timestamp is generated and included with the data sample.

Fig. 2. Sensors layout. 9 ultrasonic sensors are used to cover the grey area in the room, where most of the occupant activities happen.

For data mining and decision making, the experimentation came in three different parts: 1) Track location, 2) Predicting Activity and 3) Predicting Behavior. For tracking location, no machine learning is required, one may know the position of a person directly from the values of the sensors.

For Activity Prediction, activities are measured on trajectories on 3 sensors and synthetic data is generated based on those values. In this research, we try to study how accurate the prediction will be for the activity and the abnormal behavior. The inputs of the intelligent system are the observations that are detected at a certain point in time, they are not a sequence of events. The evaluation has shown that it is possible to accurately predict a resident's activity and detect an anomaly behavior based only on the sensor value, duration on each sensor and the range time of day

Two different data sets are used with different sets. For the first set, the behaviours are “abnormal”, “normal” and “no activity”. For the second set, the activities are “no activity”, “sitting”, “standing”, “laying”, “walking” and “running” for the second one. Each training data set has 20 attributes (Time, S1, ..., S9, Duration Sensor 1, ..., Duration Sensor 9 and Behavior). First set has 1953 instances and second one has 1486.

Actual sensor readings were used to define occupant states and Table 1 shows the combination of these 9 sensors to determine on the activities. From the change of state of sensors over time activities are defined. “Duration Sensor” attribute is used to capture, in second, how long a sensor state remains unchanged. This is used to show for how long each sensor holds a value during an activity. Behaviour is the class attribute in both data sets, it classifies the readings into activities. The time attribute of sensor readings is not the exact time, but a time range, which ranges from seconds to minutes to hours depending on rules for each sensor reading a different time is displayed.

Different classifiers were run through Weka, a data mining open source tool, focusing on accuracy, recall, precision and ROC area.

Table 1. The observations used in the proposed smart system

Sensors	Threshold	Activity
S1, S2, S5, S7	$850 < x < 940$	No activity
S3, S4	$730 < x < 760$	No activity on couch
S9	$630 < x < 650$	No activity on table
S6, S8	$720 < x < 740$	No activity on chair
S1	$815 < x < 835$	Abnormal, laying on ground
S8, S9	$600 < x < 625$	Abnormal, on the desk
S8, S9	$100 < x < 110$	Abnormal, standing on chair
S9	$30 < x < 55$	Abnormal, standing on table
S1	$265 < x < 280$	Abnormal if duration > 15 min, standing
S3, S4	$665 < x < 685$	Abnormal if duration > 4 hours, laying on couch
S1	$265 < x < 280$	Abnormal
S5 (2sec later)	$265 < x < 280$	
S1	$265 < x < 280$	Abnormal, running
S5 (1sec later)	$265 < x < 280$	
S1, S8	$430 < x < 440$	Normal, sitting in chair
S6, S8	$430 < x < 440$	Normal, sitting on chair
S1	$265 < x < 280$	Normal, duration < 15 min
S1	$230 < x < 280$	Normal, walking
S5 (2sec later)	$230 < x < 280$	
S3, S4	$665 < x < 685$	Normal, laying on couch
S3, S4	$515 < x < 540$	Normal, sitting on couch
S1	$265 < x < 280$	Normal, between 6am to 11pm
S5 (2sec later)	$265 < x < 280$	
S1	$600 < x < 625$	Normal, duration < 15min, sitting on floor

Normal activity and No activity have more instances compared to abnormal activity when the number of instances splits into activities. This is because a room is more likely to have no activity, or a person is more likely to be carrying out normal activity compared to abnormal activity.

Figure 3 represents how each type of instance for the class attribute (Activities) are divided. Most instances are categorized as No activity, Standing and Sitting. Laying, Walking and Running have less compared to the others. The reason for this distribution is because a person is more likely to sit and stand in a room and there is a high chance of no activity happening in the room. A person is less likely laying, walking or running in the room.

Name: Behaviour		Type: Nominal	
Missing: 0 (0%)		Distinct: 6	
		Unique: 0 (0%)	
No.	Label	Count	Weight
1	No Activity	262	262.0
2	Standing	304	304.0
3	Laying	180	180.0
4	Sitting	427	427.0
5	Walking	193	193.0
6	Running	120	120.0

Fig 3. The classification of class attribute Activities

Fig. 4. Scatter plot of instances classified as Normal, Abnormal and No Activities based on the sensor value observed in S9

The values produced by some sensors can be used to clearly distinguish the resident's activities and behaviours, which allow data classification and create an accurate model. For instance, as shown in Figure 4, the abnormal activities for S9 can be easily detected if the sensors produced a low value as it signifies that the resident is standing on the table. The majority of the sensor values are high because most of the time there is no one under that sensor (i.e. no activity), which also contributes to the false negatives. Figure 5 shows that the laying down activity is the easiest to detect as its produced the longest observed duration. The different colours differentiate each different type of instance in the class attribute. From the data we can see the colours are not overlapping with each other that much and there are only a few colours that cross into other territories.

Fig. 5. Scatter plot of instances classified as No activity, Standing, Laying, Sitting, Walking and Running based on the duration value observed in S1

Weka is used to create a model and train it using the datasets. Validation and test dataset are used to evaluate the performance of our trained model. The results are combined to check the integrity of the entire dataset and whether the classifier/s are providing accurate results. Cross validation is used to evaluate the predictive models.

The top 3 classifiers chosen to be compared for the first and second dataset are PART, Lazy IBK and Lazy KStar. The IBK model shows the best percentages of correctly classified instances for the first dataset at classifying behaviours, as shown in Table 2. ROC area is found out to have a very high average. Training, Validation and Test results for Data Set A are also shown in the table. Meanwhile, Lazy KStar is the best classifier for the second dataset, as shown in Table 3.

Table 2. The top 3 classifiers ART, Lazy IBK and Lazy KStar for data set A

Training Data Set A					
	CCI %	rms error	No Activity	ROC Area	
				Abnormal	Normal
PART	86.2471	0.2599	0.987	0.942	0.927
Lazy IBK	87.1795	0.2877	0.972	0.899	0.88
Lazy KSTAR	86.014	0.293	0.989	0.894	0.941
Validation Data Set A					
	CCI %	rms error	No Activity	ROC Area	
				Abnormal	Normal
PART	83.7349	0.2699	0.983	0.918	0.914
Lazy IBK	87.0482	0.2865	0.961	0.883	0.882
Lazy KSTAR	84.3373	0.3073	0.988	0.869	0.939
Test Data Set A					
	CCI %	rms error	No Activity	ROC Area	
				Abnormal	Normal
PART	84.4311	0.2773	0.982	0.927	0.914
Lazy IBK	86.2275	0.3011	0.978	0.912	0.877
Lazy KSTAR	84.4311	0.3047	0.983	0.887	0.939

Table 3. The top 3 classifiers ART, Lazy IBK and Lazy KStar for data set B.

Training Data Set B								
	CCI %	rms error	No Activity	Standing	ROC Area			
					Laying	Sitting	Walking	Running
PART	83.828	0.1907	0.945	0.992	0.999	0.999	0.842	0.927
Lazy IBK	81.9857	0.2438	0.96	0.834	1	0.926	0.628	0.803
Lazy KSTAR	89.9693	0.1746	0.987	0.991	1	0.997	0.959	0.931
Validation Data Set B								
	CCI %	rms error	No Activity	Standing	ROC Area			
					Laying	Sitting	Walking	Running
PART	85.8268	0.1969	0.967	1	1	1	0.928	0.783
Lazy IBK	79.9213	0.2543	0.985	0.861	1	0.926	0.701	0.673
Lazy KSTAR	89.7638	0.1769	0.991	0.998	1	0.999	0.944	0.813
Test Data Set B								
	CCI %	rms error	No Activity	Standing	ROC Area			
					Laying	Sitting	Walking	Running
PART	87.451	0.1718	0.965	1	1	1	0.954	0.852
Lazy IBK	79.2157	0.2626	0.98	0.862	1	0.911	0.664	0.668
Lazy KSTAR	89.8039	0.179	0.989	0.999	1	0.998	0.953	0.978

4 Conclusion

In this paper we proposed a smart house for residents of supported needs to allow them live as independent as possible by their own, with minimum interference from caregivers. Several IoT sensors are proposed to monitor the activities and the behaviour of the resident, including ultrasonic, pressure, water flow and electricity flow. To preserve the privacy of the resident and to make sure that their behaviour stays as normal as possible, all these sensors should be hidden and blended with the surrounding environment. In addition, no cameras or any recording mechanisms are used. The readings from different sensors are collected through microcontrollers and wirelessly communicated to a server over a cloud, where processing using data mining algorithms is used to determine on the behaviour of the occupant. To monitor these activities and behaviours, a web-based dashboard is created, when caregivers can access. If an abnormal behaviour is detected, then an alert will notify the caregiver to take action.

To prove the proposed concept, the paper showed a prototype of the system using ultrasonic sensors installed on the ceiling of a room. 9 sensors are installed in a room to cover the areas that most of the activities take place. Readings from the sensors are published through Arduino ESP32 microcontroller via MQTT protocol to a MQTT broker, and then stored in a SQLite3 database. For the data mining part, three different parts are considered: 1) Track the location, which does not need any datamining, since it can be determined directly from the sensors, 2) Predicting Activity and 3) Predicting Behaviour. The time attribute is also considered to predict the activities and behaviours.

Different activities are considered: “no activity”, “sitting”, “standing”, “laying”, “walking” and “running”, and different behaviours are considered: “abnormal”, “normal” and “no activity”. Datamining algorithms are applied using Weka to determine the activities and behaviours. For behaviours classification, the top 3 classifiers that give more than 84% accuracy are PART, Lazy IBK and Lazy KStar. For activities classification, again same top 3 classifiers give accuracy more than 80%.

The next step in this project, is to include other types of sensors, such as pressure sensors, water flow sensors, electricity sensors, and other sensors, to increase the accuracy of the prediction process for the activities and behaviours of the house occupant. Also, by studying the activities of the occupant we should be able to distinguish between the current house occupant and another person, such as the caregiver.

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