Human Behavior Prediction Though Noninvasive and Privacy-Preserving Internet of Things (IoT) Assisted Monitoring

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***Abstract*—As the supporting technologies for Ambient Assistant Living (AAL) in Internet of Things (IoT) domain have become more powerful and more attractive, the related systems will be widely deployed and put into action. With all associated embedded IoT sensing devices, how to maintain users' privacy and data security is a highly concerned problem. There are generally two approaches to protect privacy. One is to implement complex security protocols to guarantee the safety of sensing, storage and data transmission. Another one is to prevent the privacy issues and concerns from the source. This proposed research will provide a concept of a framework that can support behaviour monitoring through noninvasive and privacy preserving sensing. The data collected, transmitted and used for analysing in this framework is sensing information with low richness. This framework aims to increase the users' perceived privacy in existing monitoring systems to avoid data over-collection and over exposure problems.**

1. Introduction

The increasing population of elderly places a high pressure on the traditional centralised healthcare. A decentralised solution that can provide context-aware and personalised healthcare services is urgently required. The user should gain healthcare skills and knowledge through the system decisions and recommendations [1].

In our ongoing project, we aim to implement a smart living system based on a cross-layer design involving application, networking and sensing layers, requiring interdisciplinary domain knowledge. This work is based on the previously proposed idea presented in [2]. The systems will not only perform event monitoring, environment sensing or data collection, it can also provide healthcare assistance through supporting smart decision and recommendation, based on the user behaviour understanding, along with e-prescribing analysis. Those decisions can be critical for efficient and effective of health treatment. The collected data can help GPs, hospitals, to learn the living habits of the users, which increases the accuracy of decisions and the effectiveness of the treatment. The experimental results can also contribute to the evidence-based public health campaigns. This project presents a high gain return with a focus placed on exploring low-cost IoT solutions for smart living, achieving active and healthy lifestyle in the era of ageing [3].

As an essential and performance critical component in the smart living system, human behavior monitoring and prediction have drawn a lot of attentions. A large body of work has been carried out in this research area. Most solutions are based on wearable sensing or video monitoring infrastructures. One common problem in existing work is that the user privacy can hardly be guaranteed. One straightforward way to protect data privacy is to implement secured channel for data collection, transmission and storage. However, it does not solve private data sensing and information over-collecting problem. For example, in many cases, people do not want to be monitored by video camera all the time even they are informed that the collected images are 100% secure and no other parties will have the access to the data. The challenge we are facing now is how to preserve people's privacy in behavior monitoring systems from the source. Future more, as GDPR has come in action, over exposing users' personal data can break the regulations.

As shown in Figure 1 [4], the data richness of the sensors decreases as the perceived privacy from the data increases. Visible video can offer the most resourceful information but also greatly expose the users' privacy. Sensor data such as vibration, ultrasonic, photoelectric and infrared motion has high perceived privacy. However, limited meaningful information can be abstract from the data due to the low data richness. This fact explains that according to our knowledge, no solutions have been proposed to utilise those types of sensing data in order to predict human behavior. The challenge exits in how we can predict and analysis human behavior only through collecting privacy perceived data. In this work-in-process paper, we propose an approach to utilise the sensor deployment pattern and the high privacy perceived sensing data to predict human behavior.

2. Proposed Methodology

The proposed system architecture for human behavior detection is shown in Figure 2. Several sensors will be deployed in the sensing space, which are connected to the WiFi gateway for data collection. The data can either be stored in the cloud or the local database. Then the researchers

978-1-5386-4980-0/19/$31.00

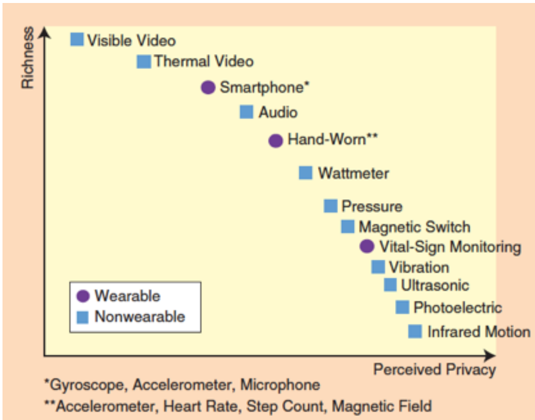

Figure 1: The richness of the sensors versus as users's perceived privacy [4]

can perform analysis on the data. The analytical results can be used to support onsite decision making and also contribute to evidence medicine.

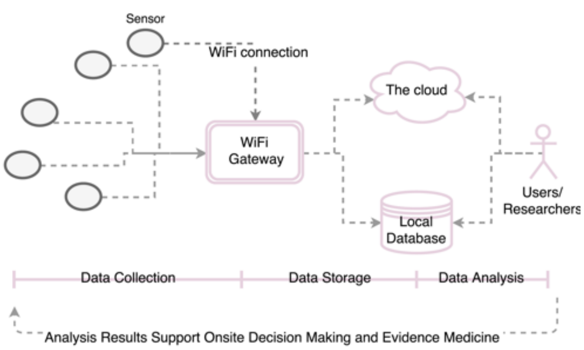

Figure 2: The architecture of the system

The working flow of the proposed research is presented in Figure 3.Firstly, during the experiment and data analysis phase, we aim to construct a demo testbed and collect data with high preserved privacy (mainly light, vibration, ultrasonic range, microphone sound detector, passive infrared motion as shown in Figure 1) and carry out data analysis along with the location information. Then through performing data analysis, we need to reveal the types of human behavior that can be detected from those collected data sets. The prediction can involve different levels of details. For example, the event can be **walking** or **walking slowly**. Secondly, based on the analysis results, we need to address whether the high preserved privacy data can provide accurate prediction in order to be implemented and used in AAL systems. If the answer if positive, we can change deployment parameters such as data collecting frequency, the sensor locations and the number of sensors and analysis of the impact of those parameters on the predict accuracy. The correlation between those factors and the analytical results will be worth to investigate and we believe there would be a fine balance between accuracy and privacy preserving degree. We also need to conclude the number of sensors and the types of sensors that can provide the best/most accurate results. However, on the other hand, if the data cannot reflect any meaningful information standalone, we then need to exam whether the results can be utilised for other existing systems to improve their privacy reservation level. Regardless of the conclusion from the second phase, possible using scenarios will be designed. At the end, based on one of using scenarios, a complete testbed will be conducted for data collection. Through analysis on the data in the finalised scenario, corresponding improvements and changes will be made to the system.

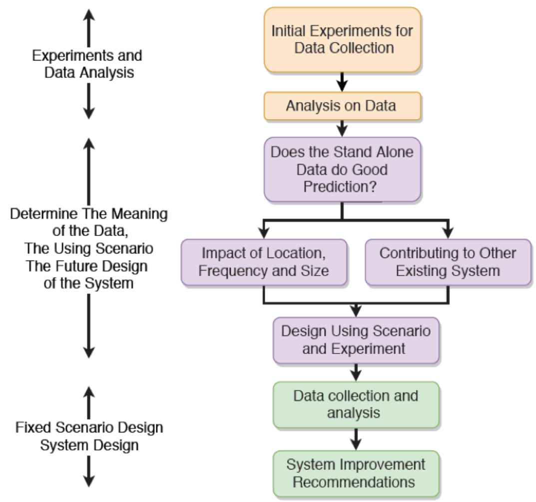

Figure 3: The designed working flow

Classification machine learning techniques can be used for data analysis to predict human behavior. However, there would be huge amount of related work on sensor data labelling. We propose that automatically labelling can be introduced to solve this problem. It is well known that behavior monitoring through visible video can already achieve a really high accuracy (over 80% accuracy) [5], [6]. Firstly, we can utilise the video information to train our privacy preserving monitoring system. There will be a camera in the system initially, collecting video data. Through analysing the video, we can then estimate the current human behavior and label the privacy preserved sensing data accordingly. After we have collected enough training data, a human behavior prediction model only based on the preserved privacy data will be activated. This automatically data labelling and training process will be a part of the auto initialisation phase of the system. After the system has been trained and the accuracy achieves to a satisfied level, the camera will be turned off and stop collecting video information. The above described process is illustrated in Figure 4. The camera and the sensors are all synchronised with the centre server. A machine learning model for behavior recognition will be firstly performed on the images from the video. The analysis results will be used to label the synchronised the sensor data set. For each sensor data entry, there would be multiple privacy preserved attributes. The labeled sensor data set will be partitioned into two sets: training set and testing/verify set.

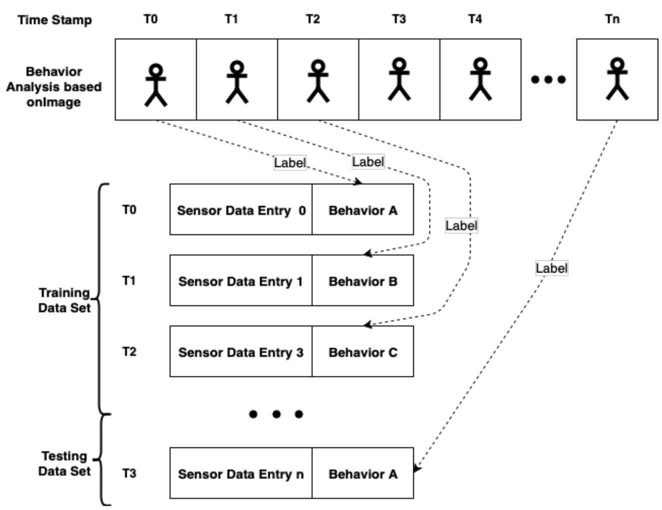

Figure 4: Auto training component for privacy preserving behavior monitoring system

3. Testbed Conduction and Data Collection

To testify our idea, one simplified testbed composed with 5 sensor motes was conducted in an office environment as shown in Figure 5. Each sensor mote was composed with 5 different types of sensors: light sensor, infrared obstacle/collision sensor, PIR motion sensor, ultrasonic ranging sensor and microphone sound detector, as shown in Figure 6. All the readings were collected as analogue values rather than digital for a better prediction model. They have been all connected with an Arduino Industrial 101 board which is enabled with a WiFi communication capability.

The data has been collected from the testbed and presented in Figure 7. We have noticed that the sensors readings are highly related to the current surroundings and their deployed locations. There are several problems related to the current testbed based on the observation of the data.

1) The sensors' sensitivity is low and sensing rage is relevantly short to cover the designed office environment.
2) Except light data, there is no clear pattern can be recognised based the data from the other types of the sensors directly.

More work should be done on selecting other types of sensors and discovering the correlations with locations. The light sensor can be used as a trigger for activity detection. The data readings for each sensor are highly related to their locations. Since the person participating in this experiment were moving around in the room most of the time, the collected data from one type of sensors, i.e, all the PIR

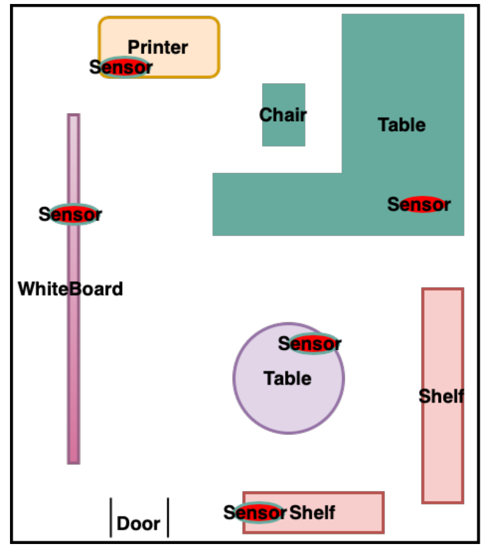

Figure 5: Deployment of the testbed in a 2m*3m office area

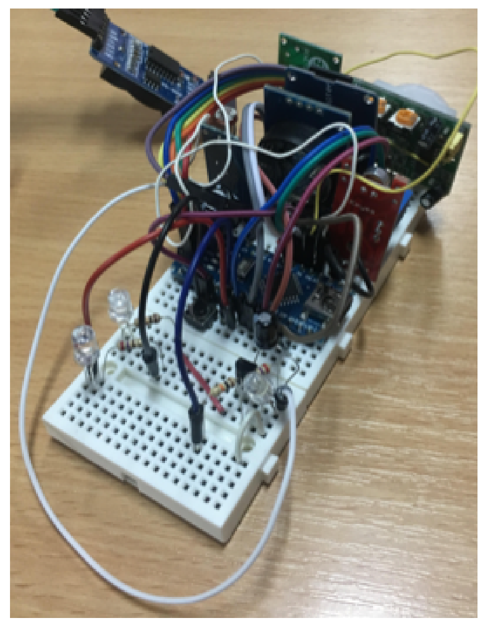

Figure 6: The composed sensor node

sensors, can be combined over the experimental period. The PIR sensor beside the door had the meaningful readings first. Thereafter the PIR besides the table starts to collecting meaningful data. Then based on the meaningful readings collaboratively collected among the sensors, we can predict the participant's movement path. According to the current results, it is hard to predict such a path only based on one type of sensor readings. Since we have not labeled the low privacy sensing data yet, the correlation between the sensors is still unknown. We expect that the underlying relationship can be used to assist behavior analysis.

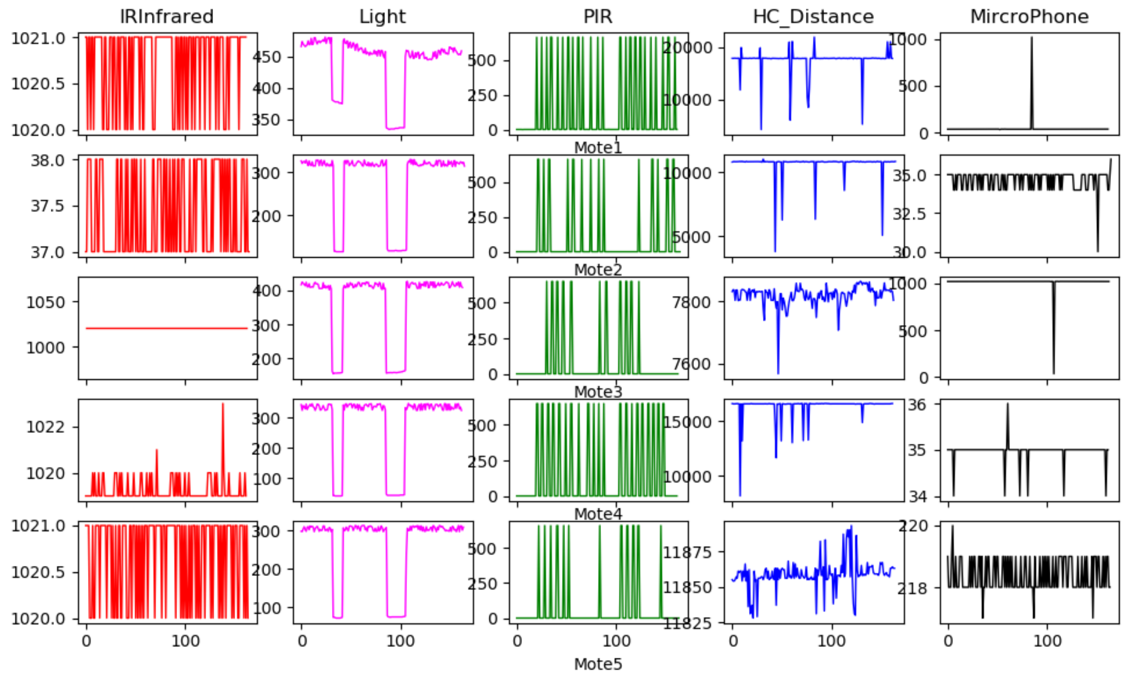

Figure 7: The results from 5 sensor nodes, each with 5 types of sensor readings: IRInfrared, light, PIR, ultrasonic range, microphone sound

4. Possible Use Case Study

There are many possible using scenarios that requires human behavior prediction. We herein propose epilepsy detection scenario. Epilepsy now is a huge health problem in Ireland [1] and worldwide [7]. Evidence medicine can highly improve the accuracy of epilepsy diagnose and then select proper treatment. We expect that our system can highly support the process.

- Before – Monitoring Generally, triggers for seizures are not the same as causes for epilepsy. Some children's seizures happen after stress, excitement, boredom, missed medication or lack of sleep. According to Epilepsy Society [2], keeping a diary of their seizures can help to see if there are any patterns when seizures happen. Once diagnosed as triggers, avoiding them as far as possible may help to reduce the number of seizures. The proposed system can facilitate to answer questions like: the person's mood, whether they make any sound and even any particular activities before the seizures.
- During – Recording The person has a seizure may not remember what has happened. It can be helpful to have a description of what happened from someone who saw the seizure, to pass on to the doctors or the specialists. Having a video recording of the seizures can even help the paediatrician understand the whole story even better. The system can trigger the pre-deployed camera and record video during the seizure. If no camera is available, the system can still can record the movements and the duration from the seizure happens till it ends.
- After – Diagnosing Since diagnosing epilepsy is not simple, doctors have gathered a lot of different information to assess the causations of seizures. The diagnosis is based on finding out what happened before, during and after the seizures. They system can record the movements and time after the seizures until the participants are back as normal.

1. https://www.epilepsy.ie
2. https://www.epilepsysociety.org.uk

5. Conclusion

Smart living systems can greatly help to decentralise healthcare demand and facilitate healthy ageing. In such systems, behavior prediction takes a huge responsibility for the quality of service. In order to improve the system performance, a large body of research has been done by utilising information rich data, such as visible video. However, the information from rich data has a high risk to over expose users' privacy. The proposed research framework in this work-in-process paper provides a behavior prediction framework through utilising the location patterns of IoT sensors and sensing data with low information richness to guarantee high perceived privacy. The prediction component initially will be trained through one of existing video behavior detection models. After achieving an expected accuracy, the camera can be turned off and the privacy preserving monitoring system thereafter will be put into action.

Acknowledgement

The authors would like to thank the following for their generouse help for this project.

- Dr. Vladimir Trajkovik, Dr. Petre Lameski and Dr. Eftim Zdravevski from Ss. Cyril and Methodius University
- Dr. Barry Cardiff from University College Dublin

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