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MEDICAL ASSIST FOR ISOLATED WARD PATIENTS IN HOSPITALS

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Abstract - Monitoring daily activities is essential for home service robots to take care of the older adults who live alone in their homes. In this article, we proposed a Medical Assist for isolated ward pateints in hospital framework by recognizing sound events in a home environment. First, the method of context-aware sound event recognition (CoSER) is developed, which uses contextual information to disambiguate sound events. The locational context of sound events is estimated by fusing the data from the distributed passive infrared (PIR) sensors deployed in the home. A two-level dynamic Bayesian network (DBN) is used to model the intratemporal and intertemporal constraints between the context and the sound events. Second, dynamic sliding time window-based human action recognition (DTW-HaR) is developed to estimate active sound event segments with their labels and durations, then infer actions and their durations. Finally, a conditional random field (CRF) model is proposed to predict human activities based on the recognized action, location, and time. We conducted experiments in our robot-integrated smart home (RiSH) testbed to evaluate the proposed framework. The obtained results show the effectiveness and accuracy of CoSER, action recognition, and human activity monitoring.

***Key Words*: Activity monitoring, context-awareness, elderly care, sound event.**

1. INTRODUCTION

The elderly population is steadily rising around the globe.

The population of 60-and-older people is projected to increasefrom 900 million in 2015 to over 2 billion in 2050 [1]. This trend leads to both economical and sociological chal- lenges in elderly care [2]. On the other hand, many older adults prefer to stay in their homes rather than move to nursing homes, although their daily living activities may become more challenging [3]. In fact, more than a third of the older adults in the USA live alone in their homes [4], which poses serious risks to them in situations such as falling or medical emergencies. Therefore, assistive technologies, such as smart homes and home service robots, are currently being developed for elderly care.

As a critical part of assisted living, human activity monitor- ing has received great interest in recent years. Camera-based human activity monitoring has been developed for manyappli- cations such as surveillance and healthcare [5], [6]. Although the vision system on a robot provides abundant information, it is not always possible to observe the resident due to occlu- sion or poor lighting. In addition, the use of cameras raises significant privacy concerns. Recently, wearable sensor-based human activity monitoring has been studied, especially for health care, military, and security applications [7]–[9]. How- ever, wearable sensors are intrusive and inconvenient if the users are required to wear them all the time. On the other hand, we know that most human daily activities generate sounds, such as eating, cooking, using the toilet, and having a shower. Therefore, it is highly desirable to equip home service robots with not only speech understanding but also sound understanding capabilities. Home sound understanding, which recognizes home sound events in the context of human daily activities, helps the robot not only monitor older adults' activities but also detect anomalies happening in the homes. Such a human-aware capability frees the robot to do its daily routine work while being able to care for the elderly more proactively and effectively.

1) A new framework for sound-based human activity mon- itoring (SoHAM) is proposed and developed which allows home service robots to better understand human daily activities.
2) A new method of CoSER is developed based on Dynamic Bayesian Networks (DBNs). This method improves recognition accuracy by considering contextual information estimated from multiple distributed sensors in a home environment.
3) A conditional random field (CRF)-based model is pro- posed to recognize human activities using the recognized action, location, and time. This method effectively over- comes the difficulties associated with the nondetermin- istic nature of complex daily activities.
4) We conducted experimental validation and evaluation of the proposed SoHAM framework in a smart home testbed using a custom-built home service robots.

2. System overview

This section gives an overview of human activity monitoring for home service robots. Our goal is to monitor human activities over time in a home environment using the audio data captured by the auditory system on the robot and the human location data estimated by the home sensor network

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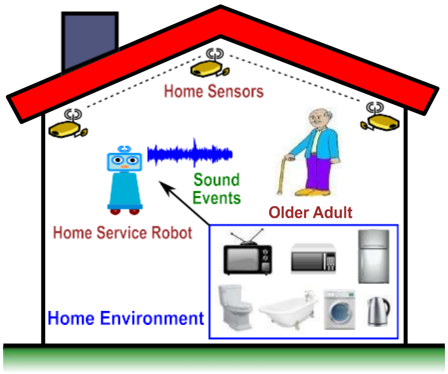


Figure -1

As illustrated in Fig. 1, a home service robot is integrated into a smart home equipped with distributed sensors that can provide information regarding human locations. This robot can capture event sounds in the home environment through its microphone array. The event sounds are recognized through a local classifier on the robot. Based on the recognized sound event and context information estimated from the home sensor network, the robot can accurately recognize human activities. The overview of the human activity monitoring system is shown in Fig. 2. The home service robot, the human localiza- tion module, and the modeling of human activity monitoring are presented in Sections III-A–III-C as follows.

A. Home Service Robot

As shown in Fig. 3, the home service robot that was developed in our Laboratory for Advanced Sensing, Computation and Control (ASCC) was built on a Pioneer P3- DX base with an approximately 1.5 m-long aluminum frame holding up a touch screen monitor which is used for video communication and graphic user interface [51]. The robot is equipped with various sensors and devices. The auditory system is built by extending the built-in microphone array of a PS3eye camera

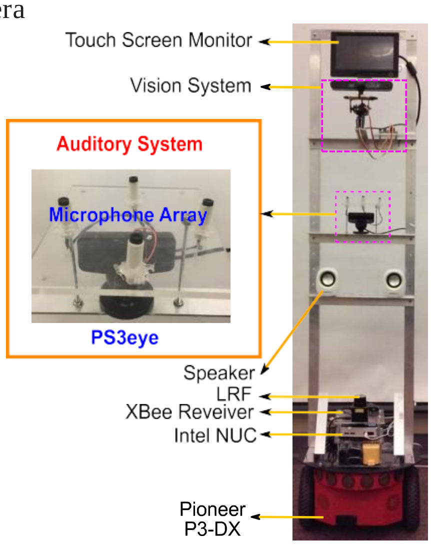


Fig:2 – Home Service Robot

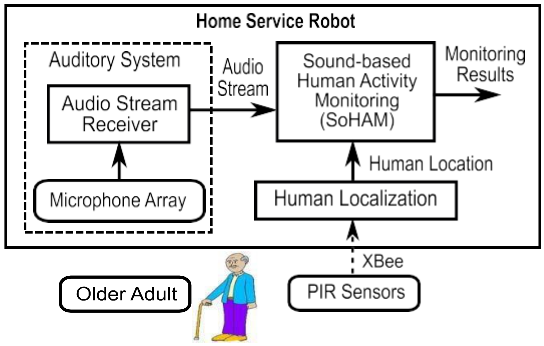


Fig. 3. Overview of the human activity monitoring system on the home service robot

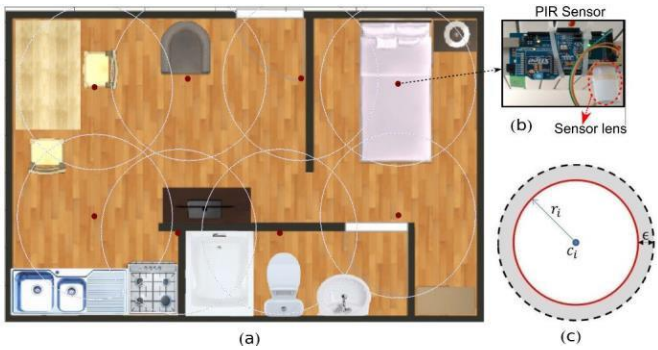
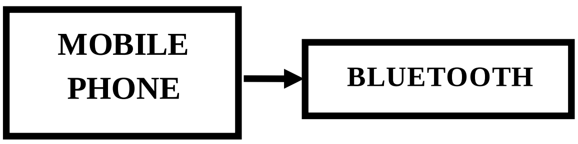


Fig. 4. (a) Configuration of the PIR network in the bestbed. (b) PIR sensor node. (c) Sensing region of a PIR node

B. Human Localization

The human localization module estimates the rough human location by using the passive infrared (PIR) sensor network deployed in the home environment. As shown in Fig. 4(a), the PIR sensor network consists of eight sensor nodes that are placed on the ceiling at a height of 8 feet and the coverage of each PIR sensor node is set to be a circle with a radius of 3.6 feet using a cylindrical lens cover. Data from these nodes are transmitted through the XBee protocol to the robot. Each PIR node detects the human motion inside its sensing region. Therefore, the human location is approximately esti- mated to be within the sensing region once the sensor gives a high output. To achieve that, a new PIR sensor observation model is developed based on the existing model.

TRANSMITTING SECTION:



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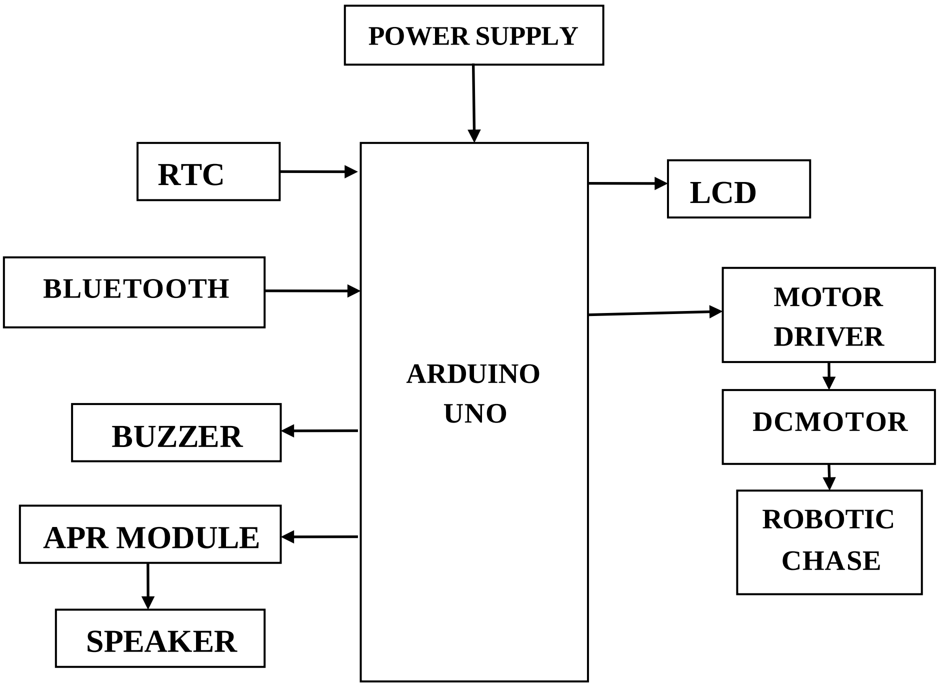

C. Working:

In this system we use ARDUINO UNO microcontroller as the brain of this proposed system so that all program coding is stored in it. Bluetooth is used to give directions to the robot. The Transmitter (mobile) will send the data to the receiving side. On the other hand the receiving side has a robotic chase and a receiver (HC-05). The receiver will get the signal and send it to the controller and the controller will send the data to the motor driver. RTC is used to monitor the time and give medicine to the patient on the scheduled time. If scheduled time occurs, buzzer will alarm. APR module is the pre-recorded voice module used to play voice for the patient about medicine in the speaker. All the information is displayed in the LCD.

D. Components Required:

HARDWARE REQUIREMENTS:

- ARDUINO UNO
- HC-05
- RTC
- MOTOR DRIVER
- ROBOTIC CHASE
- DC MOTOR
- LCD
- BUZZER

SOFTWARE REQUIREMENTS:

- EMBEDDED C

ARDUINO IDE

3. CONCLUSIONS AND FUTURE PLANS AND IMPLEMENTATIONS:

In this research, we proposed and developed a framework of Medical assist for isolated ward patients and for home service robots. The framework consists of the CoSER module, the dynamic time window-based human action recognition (DTW-HaR) module, and the CRF-based activity monitoring module. In the CoSER, the locational context of sound events associated with human daily activities is recognized based on the PIR network. The audio stream of sound events in the home environment is captured by the robot and extracted into feature vectors. Based on the context and sound event observations, the robot can recognize the sound events in real-time through a two-level DBN model using the short-time Viterbi algorithm. We tested and evaluated the framework with different parameters of the VQ and the DBN. We also proposed an algorithm called DTW-HaR to observe the sequence of sound event labels from the CoSER to estimate the current action, the duration of activity, the quality of monitoring, and the criticalness of action. A CRF model was implemented to recognize human activities based on the sequences of recognized actions. Experimental evaluation verified that our proposed framework can improve sound-based activity monitoring significantly.

In the future, we will address some limitations in the current work. First, we will keep collecting new sound data and build a larger home sound dataset with more data variations, including sound events with very short durations. This dataset will be made available to the research community. Second, machine learning methods for identifying the criticalness of each activity will be investigated, which can reduce human involvement to the minimum. Third, the proposed CRF-HAM will be enhanced to handle multiple unexpected transitions. Fourth, the proposed SoHAM framework can also be applied to distributed microphones in a smart home setting. We will compare the performance of these two microphone setups. Fifth, we will investigate how to leverage robot mobility to improve activity recognition accuracy. Finally, we will develop applications that can deliver elderly care services in response to recognized human activities.

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