A Smart System for Elderly Care using IoT and Mobile Technologies

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ABSTRACT

Population aging is becoming a pressing issue for society. The number of elderly people, those aged 60 years and over, is increasing dramatically in many countries. A great number of elderly people stay alone at home while young people in their family go out to work. This paper presents a smart system designed and developed for elderly care using IoT and mobile technologies. The features of the system include acoustic-based and accelerometer-based fall detection, real-time remote video monitoring on mobile devices, voice commands and heart rate monitoring. The evaluation matrix shows that the accuracy, precision and recall of the accelerometer-based approach were 93.3%, 92.6% and 94.3%, respectively, while the acoustic-based approach achieved 78.6%, 76.9% and 80.6%, respectively.

CCS Concepts

• **Applied computing → Health care information systems** • **Human-centered computing → Smartphones.**

Keywords

Elderly Care, IoT for Elderly Care, Fall Detection, Elderly Monitoring, Elderly Assistance

1. INTRODUCTION

Population aging is a shift of the mean or median ages of a population towards older ages. It is an interesting issue that is widespread across the world since the elderly population, those aged 60 years and older, is increasing dramatically in many countries [1], [2]. Researchers state that a great number of elderly people stay alone at home while young people in their family go out to work [3]. The number of people aged 60 and older in Thailand now stands at about ten million, accounting for 17% of the population. By 2035, Thailand's aging population is expected to increase to twenty-two million, accounting for 26% of the population [4].

Fall occurrences in the elderly as well as patients, can be categorized as follows: a fall from sleeping (bed), a fall from sitting (chair), a fall from standing or walking and fall from the support such as stairs or a ladder. The first three occurrences mainly occur in the elderly [5]. Most falls occur on flat surfaces, on the stairs or in the bathroom [6]. In Thailand, a report shows that 60% of people aged 75 and older have experiences related to fall accidents. Many of them fall and lie on the floor for hours; half will be dead within six months [6] and nearly 1,600 people die each year [7]. To prevent this loss, a health care organization suggested that elderly people should not be alone at home [8]. A caregiver should be provided to assist them in some activities, such as bathing, at meal times and using a toilet.

Internet of Things (IoT) technologies are able to provide more safety for the elderly, reducing the amount of resources needed for individual care and offering remote video monitoring, fall detection, pulse detection and alerts. However, it should not interfere greatly with a user's activities.

In this paper, we propose a system using IoT and mobile technologies to monitor and detect the falls of the elderly. The system is comprised of a Raspberry Pi 3B+ as a home unit, a small remote module, an accelerometer module, a microphone with sound card for acoustic-based fall detection and voice commands, and a camera to allow a caregiver or relatives to watch the elderly person remotely in real-time.

2. RELATED WORK

2.1 IoT Systems

IoT has enabled the automation of many processes such as sensing, communicating, interacting and collaborating with other things. It acquires input from the sensors, then it automatically manipulates the output based on the logic of the system. Body sensors were the most implemented sensors, followed by ambient sensors and fall detection. Application also dealt with providing help and video monitoring [9] [10]. Kale et al. [11] propose a health monitoring system using Raspberry Pi with Wireless Body Area Sensor Network (WBASN). The sensors included a temperature sensor, blood sensor and heart beat sensor. They were placed on a human body without disturbing the daily activities of the human. The architecture was comprised of Raspberry Pi and sensors, an Apache server as a middle layer, an Amazon EC2 private cloud server as a backend and mobile devices as a presentation tier.

2.2 Fall Detection Approaches

Fall detection approaches can be classified into three major categories depending on the sensors and detection methods [12] [13]. 1) The first, the accelerometer-based approach, employs a

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device called an accelerometer and/or a gyroscope to measure the acceleration of the body or parts of the body. The vector force generated by the devices is processed by a processing unit. If it exceeds a threshold or matches the falling pattern, the system will send a signal to the monitoring devices. In this approach, a wearable device or a sensor must be placed on the user's body or parts of the body. Due to the advancement of technology, these devices are extremely small, reliable and high-sensitivity, but they have low-power consumption. Dai et al. [14] propose a fall detection method using an android-based smartphone. They designed two algorithms for the system. The first used an acceleration-based method while the second exploited a certain device to capture human behavior using shape context and the Hausdorff distance.

The second approach, the camera-based approach, employs cameras generally installed on the wall or the place near the object of detection. Cameras have advantages over other sensor-based approaches. They can be used to detect multiple events with less interruption [13] [15]. With an inactivity detection algorithm, if the system detects that the person lies down on the floor and remains inactive for a specific period, which relates to with the LIST3 [5], the system predicts that a fall has happened. Sumiya et al. [16] use a kinetic camera and a robot to detect falls. The system includes a kinetic camera and a robot that can move to the person to detect a fall. Kepski and Kwolek [17] implement a fall detection system using a ceiling-mounted stereo 3D camera. The camera acquires a depth image capturing the detected person, called a 3D image. It is then analyzed to find the body area and identify the body's orientation. If the body is laid on the floor and remains inactive in certain contexts, a fall is detected.

The third approach, the ambient/fusion approach, is categorized into vibration and acoustic approaches. In the vibration approach, some sensors are placed in the floor where the person lives, to track vibrations, while a sound sensor or high-sensitivity microphone with sound card is used to acquire sound signals in the acoustic approach [18].

2.3 Keyword Spotting (KWS)

Nowadays, speech-related technologies are used in daily life. It enables voice commands on a smart device such as Google Now, Apple's Siri, Microsoft's Cortana and Amazon's Alexa. Users are able to control or order a system to perform a specific task by saying a word or short phrase such as "turn on"," turn off" or "I need help". Keyword spotting (KWS) is the major component for enabling speech-based user interactions including voice commands and control on smart devices. It focuses on a short phrase and requires real-time response and high accuracy to ensure a good user experience. Recently, neural networks have become an attractive choice for KWS architecture because of their superior accuracy compared to traditional speech-processing algorithms. Convolution neural networks (CNNs), composing of a stack of convolutional modules that perform feature extraction for small-footprint KWS, has been purposed by [19]. They explore two different applications: 1) the number of multiplications of the KWS system is limited; and 2) the number of parameters is limited. The results show that this approach offered 27-44% relative improvement in false reject rate compared to a deep neural network (DNN).

2.4 TensorFlow

TensorFlow is a multipurpose open source software library released by the Google Brain team to make it easier for developers to design, build, and train deep learning models applicable to a much wider range of problems [20]. It is also used for machine learning applications such as neural networks including KWS. TensorFlow is available on 64-bit Linux, macOS, Windows and mobile computing platforms including Android and iOS. Its flexible architecture allows for the easy deployment of computation across a variety of platforms (CPU, GPU, TPU), from desktops to clusters of servers, and from a computer to mobile and single-board computer for IoT applications. A developer is able to easily build neural networks line-by-line.

3. SYSTEM ANALYSIS AND DESIGN

3.1 Stakeholders

The system is designed to help the elderly and patients who need a caregiver. However, we define stakeholders according to their concerns into the following groups: 1) elderly people, 2) relatives who are more likely to be employed outside home and 3) caregiver/local volunteers who are responsible for assisting or looking after another person in daily life, for example, an elderly person or a patient.

3.2 Requirement Gathering and Analysis

The requirements for the system were analyzed and concluded from the information gathered from fifty-five families by in-depth interviews under the requirement engineering framework [10] [11]. Each family has an elderly person and relatives who are employed outside the home. The following are conclusions of the specified functional requirements in the terms of actions and functions:

- Some families have members who have retired from work and are unemployed. They stay at home and can be a local volunteer or caregiver. The local volunteers in a housing estate or housing development can be a caregiver who takes care of up to six to eight elder people that live nearby.
- The elderly aged 70 and over and the patients who cannot help themselves need assistance doing certain everyday tasks such as bathing, getting dressed, eating meals, using the toilet, going for a walk for a short period, taking medications, housekeeping or other individual needs. There are caregiver services available in the surrounding area but the hiring rate is expensive. It is not affordable for some families. However, if there is a low-cost caregiving service managed by a caregiver who lives in the same housing estate, they prefer to use it, even if it is part-time (shared caregiving service), since it is more trusted than using a service from a stranger.

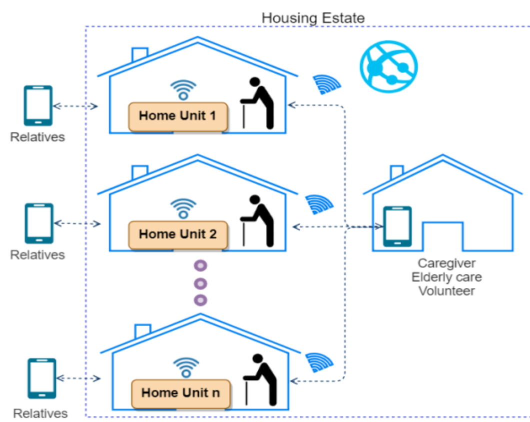

Figure 1. System Overview

- A caregiver is shared, thus, he/she will not stay with the elderly all the time. The system should provide an easy method to call for help, e.g., a small remote unit hung round the neck that the elderly person can take everywhere with them.
- The family members who work outside the home need to watch over and monitor their elderly relatives at any time using a mobile device and a real-time video camera located at home.
- The system should automatically monitor pulse rate and detect falls. It should then alert the caregiver's and relatives' mobile devices if a serious event occurs, i.e. a fall detected or weak/absent pulse detected.
- Caregivers prefer to use a mobile device to receive alerts and calls for help, and need to access a real-time video camera with access controls for privacy.

4. SYSTEM ARCHITECTURE

4.1 Purposed Solution and System Overview

As stated earlier, some families have members who can act as caregivers and the elderly usually prefer a caregiver who lives either in the same housing estate or nearby. The proposed solution is a service using IoT and mobile technologies managed by a caregiver living in the same housing estate, as shown in Figure 1.

4.2 System Architecture

This section describes the system architecture and the components that employ the IoT and mobile technologies, as shown in Figure 2. It is comprised of a home unit and mobile devices.

4.2.1 Home Unit

A home unit is located in an elderly person's home; it is comprised of input modules/devices, and processing devices that output notifications, control signals and VDO streaming to the mobile devices held by a caregiver and relatives.

4.2.2 Mobile Devices

In this system, mobile devices are used to receive notifications from the home unit; for instance, when an elderly person falls, they press a button on a remote unit or say a keyword or voice command to call a caregiver/volunteer to help (call for help as a patient means calling a nurse at a hospital).

A caregiver/elderly care volunteer's device is able to receive notifications and monitor the elderly people that he/she is responsible for (one to many). Each home unit needs to set the permission rules to allow the caregiver to access the home unit system.

4.3 Hardware Configuration

The hardware used in the system includes processors, input units and mobile devices.

- A Raspberry Pi 3B or 3B+: This is used as a main processor running on the Raspbian operating system. It is connected to a camera module for real-time video streaming and a high sensitivity microphone via a sound card.
- An MCU, NodeMCU ESP8266: A small, low-power microcontroller with Wi-Fi module is used as a micro-processor/controller receiving a signal from the accelerometer and a remote module (four-channel pendant transmitter).
- A Pi camera module or USB webcam: This is used to capture pictures and real-time video streaming. The video is broadcast live via VDO streaming software, Motion. There are two versions of the camera available, normal and night vision with infrared LED that allows the camera to see things even in the dark.
- An accelerometer module, ADXL335: A tiny, thin, low-power, 3-axis accelerometer module with high resolution (13-bit) measurement up to +/-16g gives the system the ability to tell which way is up. It has independent X, Y and Z axes and outputs 16-bit twos complement through either an SPI or IIC interface. It even has a "zero G" output to detect when the device is in free-fall and provides an interrupt to the main system to react immediately.

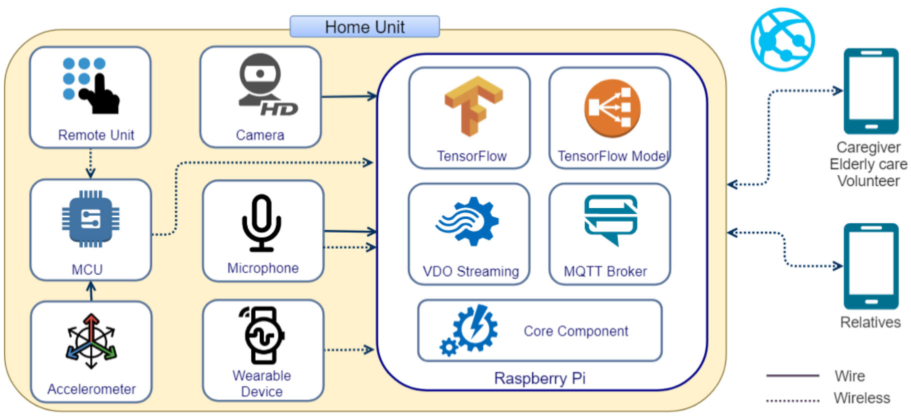

Figure 2. System Architecture

- A four-channel pendant transmitter: An RF remote module has four buttons corresponding to the four functions of the receiver connected to the MCU. It is used for multi-purpose functions. The four buttons on the remote module can be configured to call the caregiver (urgent call or not urgent) or turn on and turn off devices without reaching them.
- A microphone with sound card: A high sensitivity microphone is preferred since it acquires input sound from fall and voice commands from the elderly person. It is placed near the elderly person.
- Android wearable service: A smartwatch running on Android Wear OS equipped with an accelerometer and a heart rate/pulse sensor, as shown in Figure 3, is used to detect falls and the pulse of the elderly person.

- An Android smartphone is used as a presentation tier to receive notifications from the home station and provide access to the main system to view real-time video regardless of time and place.

Figure 3. Smartwatch

4.4 Software and Services

The home unit system exploits software and services as follows:

- TensorFlow: It is software for machine learning. In this system, TensorFlow is used to train a model and classify the input signals from an accelerometer and sound acquired from the microphone to detect falls and voice commands.

- Motion: It is a highly configurable program that monitors video signals from many types of cameras. The key features include unlimited cameras and microphones (including CSI interface and USB cameras), motion detection and remote access. It is able to detect if a significant part of the picture has changed. In this system, it is used for video streaming. The end video streams can be viewed from a mobile application implementing WebView as the layout interface.

- Mosquito MQTT broker: It is a lightweight, robust message server that implements MQTT protocol version 3.1 and 3.1.1. MQTT is designed for Machine-to-Machine (M2M) applications and IoT. In this system, the MQTT broker acts as a notification server receiving messages from the core component, and then pushes them to the mobile devices held by relatives and/or a caregiver.

5. IMPLEMENTATION

5.1 MODEL TRAINING

This system utilizes machine learning to classify the fall signal from the sensors and voice commands from the microphone. Training the model is required. In this research, the model is divided into 1) acoustic-based and 2) accelerometer based.

5.1.1 Acoustic-based Training

In this research, there are two groups of dataset: fall sounds gathered from [21] and voice command sounds collected through recordings of elderly voices saying, for example, "need help", "urgent help", "turn on the light" and "turn off" (in local language). Both groups are in WMA format. The algorithm used in this research is CNNs for KWS. The output class includes fall, not fall, idle, voice command 1, voice command 2, etc., and command n. Fall is used for an alert, but voice commands are used to send a notification to a caregiver ("need help", "urgent help") and controlling devices such as "turn on" or "off".

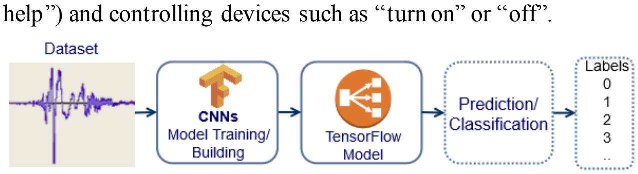

Figure 4. Acoustic-based Model Training using a CNN

5.1.2 Accelerometer-based Training

The system needs a model to classify a fall signal detected by an accelerometer and a wearable device attached to the elderly person. In this research, we employed a decision tree approach [22]. The dataset was collected from [21]. The training process was performed by TensorFlow as shown in Figure 4. The output classes were fall and not fall.

5.2 Wearable Device and Pulse Detection

We used an Android smartwatch as a wearable device. It was worn on the wrist of the elderly person. The smartwatch itself is able to run stand-alone without a companion smartphone. It is equipped with a pulse sensor and accelerometer that is able to send the signals directly to the main system over the Wi-Fi.

5.3 Mobile Client

In this research, mobile devices are held by a caregiver and relatives to receive alerts and to watch the elderly person remotely. An MQTT client background service running on a separated thread is implemented in order to perform subscribe and publish messages to the MQTT broker. This service is able to perform long-running operations.

6. SCENARIOS

This section describes possible scenarios and the workflow of the system.

- Fall detection: There are two approaches to detect a fall: Acoustic-based and accelerometer-based approaches. In the acoustic-based approach, the sound (WMA) is captured by the high-sensitivity microphone and the sound card. It is then analyzed by the TensorFlow classifier. For the accelerometer-based approach, the gravitational force (G forces) and moving velocity information are captured by a wearable device and accelerometer sensor. The wearable device is able to send the information directly to the main system via Wi-Fi.

- Need help and voice command: An elderly person is able to initiate commands via two methods: by pressing a button on a four-channel pendant transmitter (remote module) or via voice commands. The voice command is an acoustic-based approach, thus it is analyzed by the TensorFlow classifier; the signal from the transmitter is digital, which is processed by the MCU.

- Pulse warning: The heart beat pulse signal measured by a wearable device is digital. It can be sent directly to the main system via Wi-Fi. If the pulse detected is weak or lower/higher than the safety threshold, the system will alert

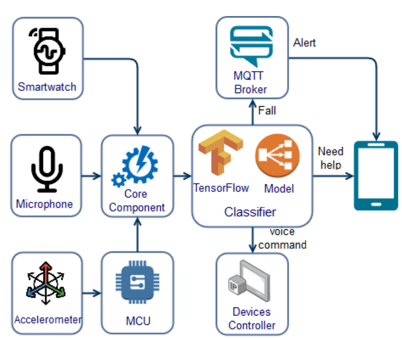

Figure 5. Fall Detection and Voice Command

the mobile devices held by a caregiver and relatives via the MQTT broker.

- Remote observation/monitoring: the caregiver and the relatives are able to watch real-time video remotely using their mobile device.

7. RESULTS

We divided the evaluation into two classes, as shown in Table 1. During the experiments, an accelerometer was placed on the user's chest and a smartwatch was worn on the wrist while the high-sensitivity microphone was placed on the floor. As shown in Table 1, the accuracy, precision and recall of the accelerometer were 93.3%, 92.6% and 94.3%, respectively. The accuracy, precision and recall of the acoustic approach were 78.6%, 76.9% and 80.6%, respectively. It appears that the accuracy and precision of the accelerometer are higher than the acoustic approach. However, even if the accuracy of the acoustic approach is lower, the elderly people prefer to use it while bathing since it is not possible to wear an accelerometer at that time.

Table 1. Evaluation

	Accuracy (%)	**Precision** (%)	**Recall (%)**
Accelerometer	93.3	92.6	94.3
Acoustic	78.6	76.9	80.6

8. CONCLUSIONS

In this study, we developed and proposed a system for elderly care using IoT and mobile technologies. The features of the system included acoustic-based and accelerometer-based fall detection, real-time remote video monitoring on mobile devices, and voice commands and heart rate monitoring. This means that the system is able to alert when a fall or abnormal pulse is detected. If the system detects a fall, the home unit will send an alert to mobile devices via a push mechanism. The mobile will sound and vibrate to warn the relatives or the caregiver. However, before calling emergency or medical staff, the caregiver can view the actual scene via the mobile device.

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