Ws-Bot: Combing Wearable Sensors and Robotic Systems to Enhance Daily Monitoring for Elder People

Yi Zhu
Computer Information Technology
Purdue University
West Lafayette, USA
zhu932@purdue.edu

Olaoluwa Oyedokun
Computer Information Technology
Purdue University
West Lafayette, USA
ooyedoku@purdue.edu

Ruiqi Wang
Computer Information Technology
Purdue University
West Lafayette, USA
wang5357@purdue.edu

***Abstract*—Elderly population is having a significant increase compared to the birthrate. Statistics from the center for disease control and prevention (CDC) state that about 8.4 million elders sustain injury from falling and 32 thousand lose their lives because of this. Due to their frailty, there is a need for them to be constantly monitored without invading their privacy to avoid them feeling uncomfortable in their own milieu. In this paper we present WS-Bot, a system that combines wearable sensors and robots to provide daily monitoring of these people. And we focus on monitoring and detecting the behavior of falling in this project. The WS-Bot consists of wearable system, robot system, and host. The wearable sensors in wearable system capture the bio-signals from the elder user, based on which the host analyzes if the user is falling or not. The robot system, which consists of a mobile robot with a camera and LIDAR oversees verifying the abnormal behavior reported from the wearable system and feedbacking updated textual and visual information. The host sends an alarm to responders based on the robot system's information. And we evaluate each part of Ws-Bot through experiments and demonstrate the feasibility of the whole system.**

Keywords—Crowdsourcing, Accessibility, Human-Computer Interaction, Human-Robot Interaction, Healthcare.

I. Introduction

Elderly people by definition from the United Nations are an age group of people from 60 years or over [8]. Reports from the studies carried out by the United Nations show that there is a rapid increase in the number of seniors compared to the number of birthrates [2]. A number of people develop complex diseases at their old age which will need the attention of other people to keep watch over them. Due to the frailty of old age, it is estimated [11], that in 2018 the number of falls from elderly people recorded was 35.6 million, out of this number 8.4 million resulted in injury while an estimated number of 32, 000 lost their lives as a result of the fall.

In most countries they employ the services of home workers to water over their frail elders, but the challenge of having home workers is that some might not have the momentary fund to continually pay them, while [3] noted that with the rate at which the number of old people are increasing at some point there will not be human capital to cater for their growing numbers. In addition because of their health challenges some are moved to elderly homes which at some time most of them don't like to stay there [1].

Therefore, there is a need to provide an alternative and better way for caring for the elderly which is the introduction of assistive technologies in their living area. Assistive technologies as defined by [4] is a device that helps perform a task an individual is to accomplish or to increase the safety at which a task is performed. Although some of the elderly individuals are respective of technologies, they don't find them interesting or easy to use.

Due to some of these challenges, we are developing a robot that will help detect their health conditions and send signals to necessary authorities. However, there are devices like smartwatches and other assistive technologies that might do something similar but these devices at some point have noise in their system and thereby release an alarm to the environment or to their caregivers. To avoid unwanted signals sent to the family of the elderly people, we are working on robots that will validate the situation before the signal is sent out.

This paper will cover literature reviews, approach, result and analysis, and future works.

II. Literature Review

A portion of the elderly population suffers from physical and cognitive impairment as reported by [5]. As a result of these conditions, a cognitive assistant called PersonAAL was created to help them. This technology made use of wearable sensors that measure any notable change in the elder's health status. The information gathered from this device is transmitted to the caregiver that oversees this elder person. However, PersonAAL suffers from the noise from the wearable sensors. Furthermore, [7] developed a wristband targeted at the physical appearance of elders, to measure their stress and emotional level. Emerald as the wristband is called captures all the data targeted at measuring the stress level and emotions. Unlike PersonAAL, Emerald could detect noise in the data collections, especially when the elder is carrying out a workout exercise which could trigger an alarm. Emerald makes use of cognitive sensitivity to measure when the exercise is going out of limit and inform the elderly with a prompt. However, Emerald arm cannot stream back any images or videos to illustrate the situation of the elder people. [6], considered a robot without the elderly individual interacting with the robot having any wearable device, this approach was carried out to reduce the level of noise generated by the wearable device. The assistive technology called PHAROS uses both robots and scheduling systems to monitor elders doing their exercise. To achieve this, the vision of the robot made use of Pepper robot, which is medium size and palatable to look so it does not scare the elderly away, the robot is in the charge of the activities assigned to the elderly and the robot uses its computer vision to capture when the elder starts and when the elder stops. This could not also detect why the elder stops but will give the caregiver information that the person stopped. Several factors might be involved for a change in the pattern of exercise that might not be related to health issues.

Another direction of monitoring elder people is to equip several types of sensors to detect any abnormal behaviors indoors. One of the research groups aimed at building an abnormal behavior detection system based on an omni-directional vision sensor [9]. The monitoring systems can learn daily behavior patterns and detect unusual behavior patterns using the Bayesian Network approach. Because of the fixed position of the camera, the system only detects people's behavior within a closed indoor environment, so this may work better with elders who stay in one room most of the time.

However, there is research showing that the elders will be concerned about the privacy issue when they realize that they are under monitoring with the standing-alone cameras [12]. As a result, they may change their behavior at home and decrease their comfort level in doing certain activities which can be involved in privacy issues but increase the comfort level of some activities that may be more dangerous for people to do in their age.[15] discussed wearable technologies that are used in monitoring the health situations, physiological conditions and motion activities of elders, which put in the arguments that in creating a wearable sensors, ergonomic conditions needs to satisfied to avoid been a burden on the user. SMARTA project, a wearable T-shirt customized with health monitoring sensors [16]. The system is designed to have sensors attached to different part of the house to monitor footsteps of the individual been monitor and to capture data from the accelerometers when an elderly person falls, but the challenge with this system is that there is no device to verify if there is a noise within the signals gotten from the wearable sensor.

In addition,[10] created Philos for the elderly living alone to engage with them to encourage their healthy lifestyle. It is a sociable robot and was developed as a wearable health monitoring device accompanied with emotional stimulation through human-robotic social interaction. The wireless health monitoring technology was integrated into it through the wearable sensor. This permits the robot to monitor the health condition of the individual and create a connection between the robot and the elderly. The sensor helps the health practitioners to monitor the state of health and act when necessary. However, the limitation with Philos shows that it monitors heart rate but might not be a case of emergency but to create an emotional gesture to the elderly also, there is lack of verification of the signal by the robot. As much as there are many existing methods for monitoring elder people, they still have limitations: the approaches that only use wearable sensors suffer from inaccurate signals from wearable sensors and ineffective information communication, while the methods only using robots suffer from limited work scenarios and potential poor user experience.

III. Approach

To solve the above described challenges of existing methods for daily eldercare monitoring, we propose Ws-Bot, an approach that combines the strengths of wearable sensors and the benefits of robotic systems to enhance daily monitoring for elder people. The wearable sensors can provide 24-7 and user-friendly monitoring for direct bio signals of elder people which is beyond the ability of robotic systems. On the other hand, robotics systems can make up for the shortcoming of wearable sensors: providing verification to help eliminate the noise signals from sensors and enable efficient information conveyance. In our case, we selected falling down as the abnormal behaviors to be detected in our system, since it is more doable for experiments than heart disaster which we cannot easily pretend.

Figure 1. illustrates the framework and workflow of our system, Ws-Bot, which consists of four parts: elder people, responders, host, wearable system, and robot system.

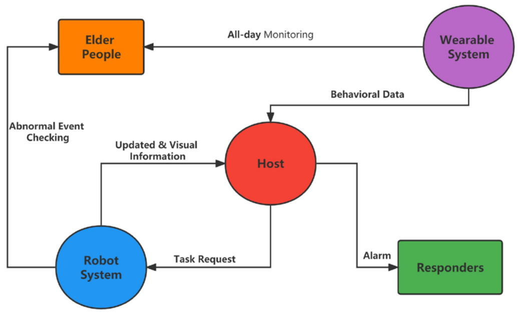


Fig. 1. Illustration of Framework.

A. Overview

The wearable system which is consisted of the wearable sensor monitors elder people 24-7 and convey the collected bio-signals to the host in real time. The host receives and analyzes the bio-signals of the elder users to predict if they fall down or not. If falling down is detected from the wearable system, the host will requests the robot system to verify the reported the event. Then the robot starts to find the elder user to check and verify the falling down event, and feedbacks the updated and visual (e.g., pictures of the user) information to the host. The host sends alarm to responders based on the information provided by the robot system.

B. Elder people

This presents an age group of people from 60 years or over which need to be monitored.

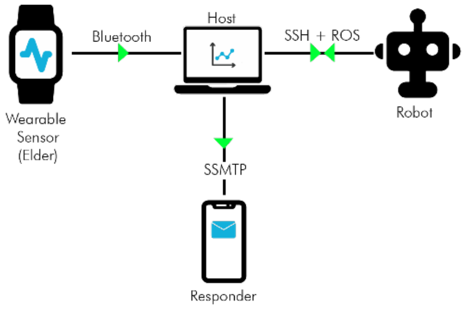
C. Responders

This refers to people who receive the alarm of emergency events of elderly people and provide help as seen in Figure 2, for example, the family members and health professionals.

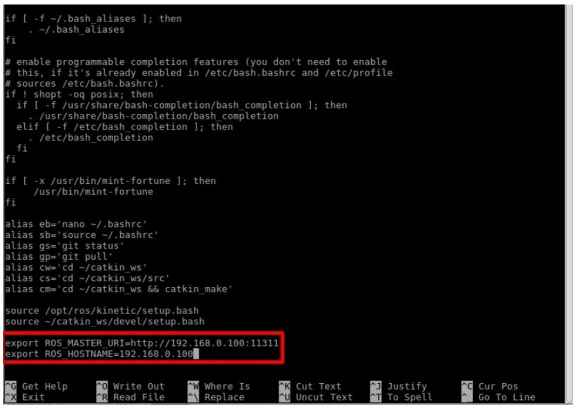
Fig.2 Screenshot of email received by a responder.

D. Host

We use a laptop as the host. The host represents the central host that serves as the bridge connecting the wearable system, the robot system and users in our system. And the potential function of the host is to provide cloud computing power for the robot system. We used a laptop as the host, and utilize SSH with ROS as the means of wireless communication between to the robot and laptop, also the connection between the wearable sensor (elder) and the host was through Bluetooth, we opted for Bluetooth to allow the elder move freely within the environment that they are. While the connection between the host and the responder was through SSMTP a package in ubuntu that can send an email directly to a predefined user through terminal. ROS which is Robot Operating System – is not an operating system but a set of software framework for robot software development, services like low level device control and functionality like message passing. SSH (Secure Shell or Secure Socket Shell) this enables us to have access to the administrator of the robot system and establish a wireless communication. Furthermore, SSMTP (Simple Mail Transport Protocol) we used it in transmitting email from one server (Host) to email client (Responders).



(a)



```
if [ -f ~/.bash_aliases ]; then
    . ~/.bash_aliases
fi

# enable programmable completion features (you don't need to enable
# this, if it's already enabled in /etc/bash.bashrc and /etc/profile
# sources /etc/bash.bashrc).
if ! shopt -oq posix; then
  if [ -f /usr/share/bash-completion/bash_completion ]; then
    . /usr/share/bash-completion/bash_completion
  elif [ -f /etc/bash_completion ]; then
    . /etc/bash_completion
  fi
fi

if [ -x /usr/bin/mint-fortune ]; then
     /usr/bin/mint-fortune
fi

alias eb='nano ~/.bashrc'
alias sb='source ~/.bashrc'
alias gs='git status'
alias gp='git pull'
alias cw='cd ~/catkin_ws'
alias cs='cd ~/catkin_ws/src'
alias cm='cd ~/catkin_ws && catkin_make'

source /opt/ros/kinetic/setup.bash
source ~/catkin_ws/devel/setup.bash

export ROS_MASTER_URI=http://192.168.0.100:11311
export ROS_HOSTNAME=192.168.0.100

^G Get Help    ^O Write Out   ^W Where Is    ^K Cut Text    ^J Justify     ^C Cur Pos
^X Exit        ^R Read File   ^\ Replace     ^U Uncut Text  ^T To Spell    ^  Go To Line
```

(b)

Fig. 3 Illustration of Host System.

E. Wearable System

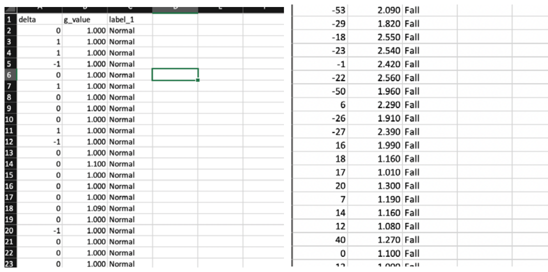
This refers to wearable sensors worn by the elder people. We utilize E4 wristband [13] (Fig.4) as the hardware in this system, and the signals captured include Heart Rate (HR), Accelerometer (ACC), Skin Temperature (SKT) and Blood Volume Pulse (BVP). ACC is used for safety monitoring (e.g., falling) while others are used for health monitoring, e.g., heart disease, fever, and cardiovascular disease.

Fig. 4. E4 wristband.

We used the cloud platform provided by the sensor for data transfer and develop some algorithms to assess the safety and health metric based on the raw data. (Fig. 5)

Fig. 5. Sample graph of sensor data.

To process the data so that the system can decide the states of the user, we apply Machine learning algorithm Support Vector Machine (SVM) to classify the normal state and falling state. SVM is a widely used algorithm for classification. In our case, the model should be built with changes in Z value and changes in g-value (acceleration) from ACC sensor data. These two values are combined as a two-element vector with shape (2,1), and label them according to the state of the user. We plan to collect some static data for labeling two states, and then build the SVM model to find the max margin between two states. We collected the data for testing the system by simulating different fall actions and different movement of hand gestures. And we repeated this process for 15 times. Before feeding the model, we pre-processed data by subtract the current Z value with the previous time stamp Z value and name the variable Delta.

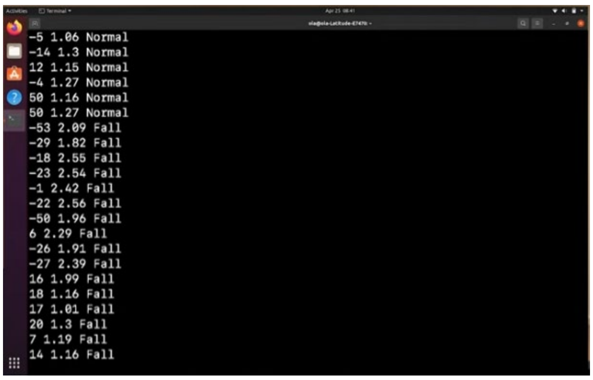


	delta	g_value	label_1
2	0	1.000	Normal
3	1	1.000	Normal
4	1	1.000	Normal
5	-1	1.000	Normal
6	0	1.000	Normal
7	1	1.000	Normal
8	0	1.000	Normal
9	0	1.000	Normal
10	0	1.000	Normal
11	1	1.000	Normal
12	-1	1.000	Normal
13	0	1.000	Normal
14	0	1.100	Normal
15	0	1.000	Normal
16	0	1.000	Normal
17	0	1.000	Normal
18	0	1.090	Normal
19	0	1.000	Normal
20	-1	1.000	Normal
21	0	1.000	Normal
22	0	1.000	Normal
23	0	1.000	Normal

-53	2.090	Fall
-29	1.820	Fall
-18	2.550	Fall
-23	2.540	Fall
-1	2.420	Fall
-22	2.560	Fall
-50	1.960	Fall
6	2.290	Fall
-26	1.910	Fall
-27	2.390	Fall
16	1.990	Fall
18	1.160	Fall
17	1.010	Fall
20	1.300	Fall
7	1.190	Fall
14	1.160	Fall
12	1.080	Fall
40	1.270	Fall
0	1.100	Fall

Fig. 6. Dataset sample for building model.

After building model with the static data, we plan to test the model when the user is wearing the wristband. In this case, the wristband will send the ACC sensor data to the host and the host will use the model to identify whether the user is in normal behavior. The result will display as figure 7.



```
-5 1.06 Normal
-14 1.3 Normal
12 1.15 Normal
-4 1.27 Normal
50 1.16 Normal
50 1.27 Normal
-53 2.09 Fall
-29 1.82 Fall
-18 2.55 Fall
-23 2.54 Fall
-1 2.42 Fall
-22 2.56 Fall
-50 1.96 Fall
6 2.29 Fall
-26 1.91 Fall
-27 2.39 Fall
16 1.99 Fall
18 1.16 Fall
17 1.01 Fall
20 1.3 Fall
7 1.19 Fall
14 1.16 Fall
```

Fig. 7. States identification sample

F. *Robot System*

We select a Jackal Mobile Robot (Fig. 8) as the equipment for the robot system. The functions of the robot system are to verify abnormal events detected by wearable system and capture and convey visual situational information for responders. To this end, the robot system has to accomplish following tasks: 1) finding the user and 2) verification of abnormal events (falling down).

Fig. 8. Jackal Mobile Robot.

For task 1, we design a robot navigation system that combines point-to-point (P2P) navigation and computer vision (CV) based navigation. The procedure of our navigation system is shown in Figure 9. The robots start to conduct P2P navigation to checkpoints in each possible area, and after reaching one checkpoint, the CV based navigation takes over to find the user. If the user is found by the CV based navigation, the navigation system stops working, if not, the P2P navigation takes over to navigate to the next checkpoint and repeat above procedures until the user is found.

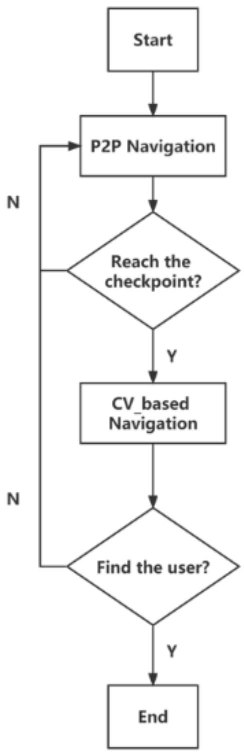


Fig. 9. Navigation system illustration.

For the P2P navigation method, we utilize the Gmapping ROS package. We built the map in Rviz, and we made use of the Adaptive Monte Carlo Localization (AMCL) to locate the robot and Move Base to navigate from point to point. We created checkpoints for us to know the direction at which the robot needs to navigate and to also know check mark if the task were completed. We recorded each checkpoint with a tuple (x, y, z, o) that presents robot's position in x-y-z axis and robot's orientation in each living area (bedroom, living room, kitchen, etc.)

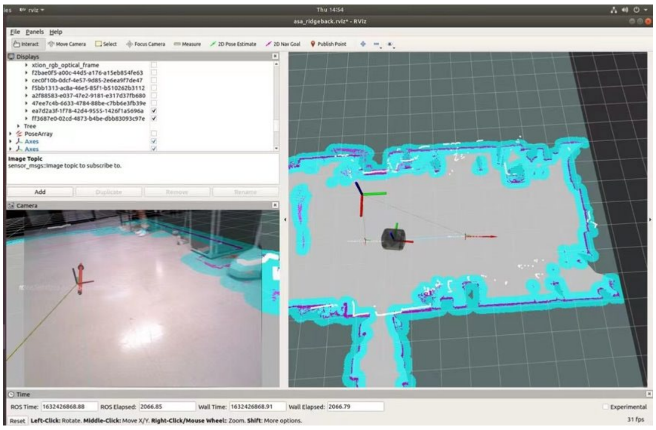
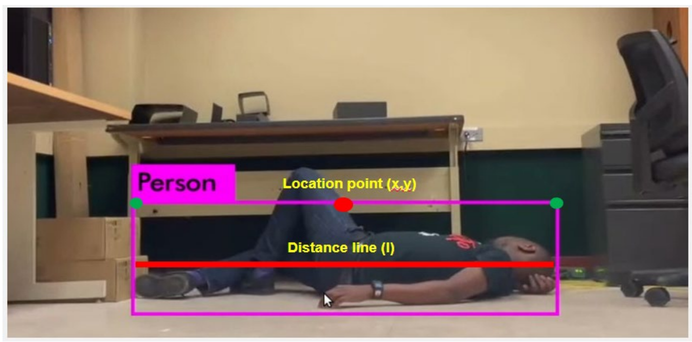


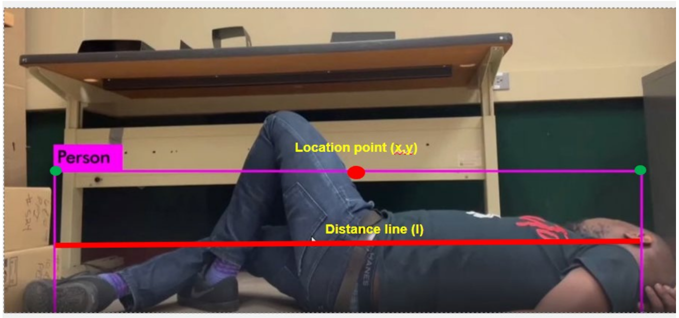
Fig. 10. Gmapping method illustration in Rviz.

For the CV based navigation method, we utilize YOLOv3 [14] to recognize the user (person) and based on the bounding box feedbacked by it we design an algorithm that enables the robot can turn it direction to face to the user and then approach the user within a certain distance. To train the recognition model, we use the INRIA Person Dataset [18]. As is shown in Figure 11, the pink box refers to the bounding box. We select two vertices (green points) of the bounding box to calculate the location point and distance. The robot turns left or right to face straightly to the user by keeping the location point in the middle of the robot view. Please note that our assumption or constrain is the camera is located in the exactly middle of the robot. Then the robot moves forward until the length of the distance line is below a threshold, which means the robot has reached a certain distance from the user. The procedure of the whole algorithm is shown in Figure 11.

For task 2, we use the Baidu human body gesture recognition API [17]. As is shown in Figure 12, the API can capture 16 key points (blue points) of a human body, such as chest, hand, leg, wrist and so on, and can automatically feedback the detected behavior, such as falling, sitting, standing and so on.



(a)



(b)

Fig. 11. CV based navigation illustration.

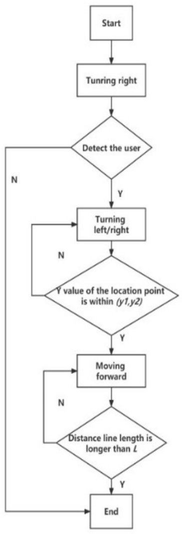
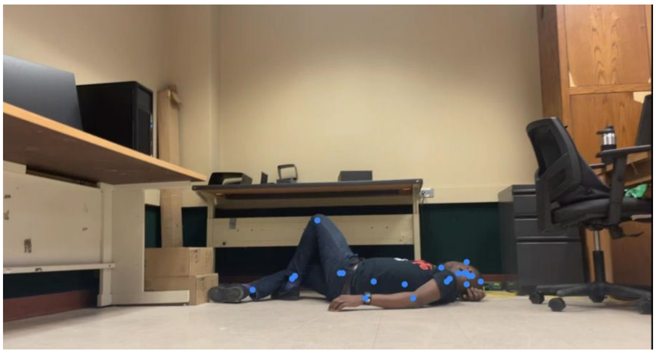
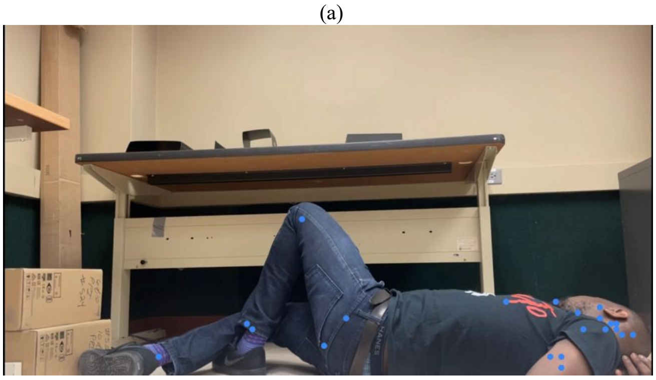


Fig. 11. Finding the user algorithm illustration.



(a)



(b)

Fig. 12. Human behavior dectection illustration.

IV. Result and Analysis

A. Wearable System

With enough static and real-time data, we first built the SVM model with statics data, and we split the dataset into 70% training data and 30% testing data. After testing several kernels to fit the model, we found the linear kernel work the best with around 0.99 accuracy in the best cases, as showing in figure 13. But when testing the real-time data, this model only successful 10 times out of 15 tries.

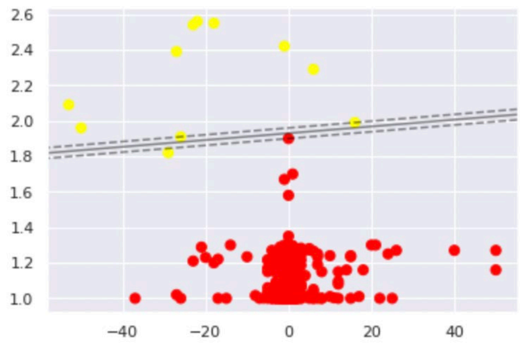


Fig. 13. SVM model with static data.

B. Robot System

For the human recognition model YOLOv3, we test it using static images that contain human, the model achieves a 100% accuracy on 50 images without screens in front of the human and 67% accuracy on 15 images with screens. For the finding people navigation algorithm, we test it for 10 times where the robot successfully finds and approaches the human for 9 times. The Baidu human body detection API is tested 10 times with a 100% accuracy. However, the recognition time has some delays as it transfers images via internet.

C. WS-Bot

We tested the whole system on the 1st floor at HEAV Hall, using Room 101 and Room 105. The experiment video can be found at: https://youtu.be/VQsI6XA3vn4

V. Future Works And Conclusion

We have developed a prototype working WS-Robot system which we will have to validate. Furthermore, we will be putting into consideration other abnormal behaviors (heart attacks, blood pressure, body temperature, etc.) to give a robust data collection. In addition, we will improve the computer vision and navigation system to suit in complex environments and introduce thermal imaging recognition system. We plan to search for some open-source API that provides text-to-sound functions.

VI. Individual Contribution

Yi Zhu worked on implementing the wearable sensor and analyzed the data set that we gathered from this study, while Ruiqi Wang worked on the computer vision of the system and the navigation of the robot system alongside with Olaoluwa Oyedokun, in addition to the contribution of Olaoluwa was to create the hosting platform for wireless communication between the robot system, wearable sensors and responders.

Furthermore, in the creation of demo video, Yi directed on what we could do to get valuable data from the wearable sensor, she also recorded the scene of the robot movement and when the elder person was falling, while Ruiqi was the responder and he calculated the checkpoint of the robot, while Olaoluwa acted as the Elderly person that need help to monitored, alongside editing the video.

REFERENCES

[1] WHO (World Health Organization) (2018), Ageing and health, available at: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health (accessed 12 February 2019).

[2] World Population Prospects 2019, Dept. Econ. Social Affairs, Population Division, United Nations, New York, NY, USA, 2019.

[3] Woll, A. & Bratteteig, T. (2019). A trajectory for technology-supported elderly care work. Computer Supported Cooperative Work (CSCW), 28(1-2), 127-168.

[4] Cowan, D. and Turner-Smith, A. 1999. The role of assistive technology in alternative models of care for older people. In Royal Commission on Long Term Care, Research Volume 2, Appendix 4, Stationery Office, London, 325–46.

[5] Martinez-Martin, E., & Costa, A. (2021). Assistive technology for elderly care: An overview. IEEE Access, 9, 92420–92430. https://doi.org/10.1109/access.2021.3092407

[6] Martinez-Martin, E., Costa, A., & Cazorla, M. (2019). Pharos 2.0—a physical assistant robot system improved. Sensors, 19(20), 4531. https://doi.org/10.3390/s19204531

[7] Rincon, J. A., Costa, A., Carrascosa, C., Novais, P., & Julian, V. (2019). Emerald—Exercise Monitoring Emotional assistant. Sensors, 19(8), 1953. https://doi.org/10.3390/s19081953.

[8] World Population Ageing 2015; Technical Report ST/ESA/SER.A/390; United Nations, Department of Economic and Social Affairs, Population Division: New York, NY, USA, 2015.

[9] S. Hirokazu and T. Susumu , “Abnormality detection monitoring system for elderly people in Sensing and robotic support room,” 2008 10th IEEE International Workshop on Advanced Motion Control, May 2008

[10] Hornfeck, K., Zhang, Y., & Lee, K. (2012). Philos. Proceedings of the 27th Annual ACM Symposium on Applied Computing - SAC '12. https://doi.org/10.1145/2245276.2245334.

[11] Moreland, B., Kakara, R., & Henry, A. (2020, July 9). Trends in nonfatal falls and fall-related injuries among adults aged ≥65 years - United States, 2012‑2018. Centers for Disease Control and Prevention. Retrieved March 4, 2022, from https://www.cdc.gov/mmwr/volumes/69/wr/mm6927a5.htm

[12] K. Caine, S. Šabanovic, and M. Carter, “The effect of monitoring by cameras and robots on the privacy enhancing behaviors of older adults,” Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction - HRI '12, pp. 343–350, Mar. 2012.

[13] E4 wristband. Online: “https://e4.empatica.com/e4-wristband.”

[14] Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).

[15] Majumder, S., Mondal, T., & Deen, M. (2017). Wearable sensors for Remote Health Monitoring. Sensors, 17(12), 130. https://doi.org/10.3390/s17010130

[16] Andreoni, G., Perego, P., & Standoli, C. (2015). Wearable monitoring of elderly in an ecologic setting: The smarta project. Proceedings of 2nd International Electronic Conference on Sensors and Applications. https://doi.org/10.3390/ecsa-2-s3001

[17] Baidu AI Human body dection api, Online, https://ai.baidu.com/tech/body/pose

[18] Taiana, M., Nascimento, J. C., & Bernardino, A. (2013, June). An improved labelling for the INRIA person data set for pedestrian detection. In Iberian Conference on Pattern Recognition and Image Analysis (pp. 286-295). Springer, Berlin, Heidelberg.