Easy-Assist: An Intelligent Haptic-based Affective framework for Assisted Living

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***Abstract*—Unlike the younger population that uses wearables such as smartwatches for monitoring health on daily basis, elderly people need assistance in the use of technology and interpreting the data obtained through these smart connected frameworks. The current monitoring systems are primarily designed to monitor the physiological signals on daily basis. The aim of this proposed research, Easy-Assist, is to help older people to maintain their emotional well-being. This research is focused on developing a wearable affective framework, which can help in detecting the emotions of the user in addition to monitoring their physiological signals. The proposed framework can be used in an automated assisted living environment, where the user's emotional state can be balanced using a haptic-based emotional elicitation system after the user's emotion is recognized, detected and interpreted in real-time. The proposed framework is validated using a fall detection algorithm deployed in a custom-built watch wearable, built using off-the-shelf components and an emotion detection framework built using a single board computer. A dataset of 21700 samples acquired using the proposed framework yielded a maximum efficiency of 97.25%, 96 %, and 94 %, in classifying the state and emotion classes into Alert, Active and Normal classes respectively, using multi-class SVM model. The overall latency of the proposed research was in few orders of milli-seconds.**

***Index terms*—** Internet of Things (IoT), Smart Healthcare, Affective computing, Assisted Living, Fall emotion

I. Introduction

The ratio of the aged-population at 60 years or above was around one in eight as of 2015. This indicated that 33 % of the Japanese population belonged to the aged-category. With this ratio increasing at a faster percentage, it is expected that by the year 2030, the elderly people will outnumber children aged 0-9 years [1]. This means that there won't be enough number of assistants or nurses to take care of the elderly population in the next decade.

The trend of using automated connected devices for easy living has been prominent in the past few years due to the applications of Internet of Things (IoT) [2]. IoT is a network of interconnected wireless devices where each device can recognize itself in the network [3]. Major applications of IoT include smart connected cities, smart healthcare, smart transportation and so on. With a large number of such connected devices and frameworks, it is easier to remotely assist those in need. Unlike the younger population that uses wearables such as smartwatches for monitoring health on daily basis, elderly people need assistance in the use of technology and interpreting the data obtained through these smart connected frameworks. In emergency scenarios where they cannot get a chance to inform their caretakers or friends and family, they need a fully automated framework that can help in creating alerts as required. In order to help such individuals with easier living, we propose a novel intelligent haptic-based Affective framework, Easy-Assist. The conceptual overview of the proposed framework is given in Figure 1. The proposed framework uses the advantages of advance computing fields such as the Internet of Things and Affective computing, to develop an assistive framework.

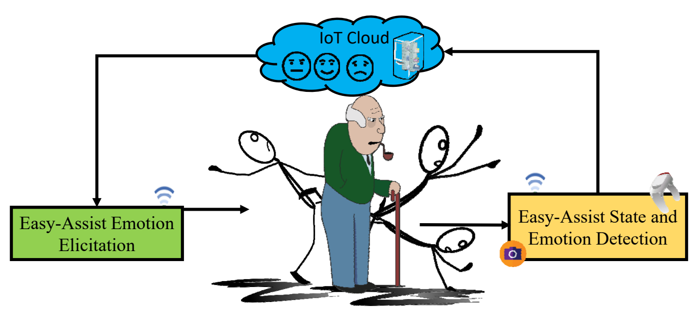


Fig. 1. Conceptual Overview of the proposed Easy-Assist system

The organization of this paper is as follows: The novel contributions of this paper are described in Section II. A broader perspective of the proposed Easy-Assist framework is presented in III. Some literature on existing research work on assisted living, modeling IoT-based smart healthcare systems and applications of affective computing is discussed in Section IV. An overview of the system-level modeling of the proposed framework with respect to fall emotion detection algorithm is given in V. The implementation of the designed blocks along with simulation results are discussed in VI. The future directions of the proposed research are outlined in VII

II. Novel Contribution

Affective computing also known as emotional artificial intelligence helps in developing systems that can detect, interpret, and stimulate human emotions. In the proposed affective computing framework, the state of the person, i.e., stand, sit, laying, walking, and fall state are recognized along with the user's emotion during these states. Older people need assistance if there is a fall or sudden shift in their state, and they need to be in normal state of mind when there is a change in one of the identified 5 states. With an aim to analyze the emotions related to these 5 states and help in balancing the emotional state of the user, the proposed Easy-Assist system is designed with following contributions:

- A novel haptic-based Affective framework for fall detection and emotion recognition has been proposed.
- A novel fall state detection algorithm along with the feedback routine has been proposed.
- A novel state and emotion detection algorithm has been proposed.
- The proposed fall detection algorithm is validated using a custom-built wearable.
- The proposed affective framework is validated using cost-effective components.

III. Easy-Assist for Assisted Living: A Broad Perspective

With the help of artificial intelligence and machine learning, machines can understand and analyze the inputs fed to them and provide well-analyzed outputs. Affective computing, a multidisciplinary branch of science that includes computer science and Engineering, Cognitive Science and Psychology, helps in stimulating human emotions after recognizing and interpreting them [4]. This helps in closing the loop by providing feedback to the user. Hence, monitoring systems designed using affective computing needs to perform emotion recognition and emotion elicitation.

The motivation for the Easy-Assist system is to develop a framework that can help in analyzing the human emotion in every state of the user. i.e. instead of merely recognizing that the user has fallen down, if the emotional state of the person during the time of fall has been recognized, accordingly the user can be encouraged to return to their normal state physically and emotionally. In this proposed assisted-living framework, the state and emotion detection is done with help of a camera and a wearable as shown in figure 2. The proposed wearable was custom-built using off-the-shelf components to detect the state of the user by monitoring the user's daily activity and heart rate. The emotion recognition part of the framework is achieved by using face recognition done with help of a camera placed in the user's environment. The primary tasks of the camera are to recognize the user's emotional state and classify them into 4 main categories: Normal, happy, panic,and annoyed. Hence, by identifying the state and emotion of the person, haptic feedback is given to the user each time to keep them informed of their health and maintain emotional balance.

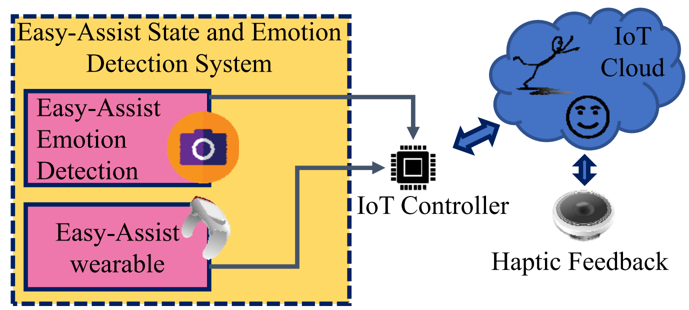


Fig. 2. An Overview of the Proposed Haptic-based Affective framework

IV. Related Prior Research

A detailed literature review on the challenges in existing technologies for elderly care has been presented in [5]. Research in affective computing has been more focused on monitoring the brain wave response during the emotion recognition and emotion elicitation phase [6]. Martin-Morales et al., have identified that the emotion elicitation module is presented either as immersive environment or passive feedback systems [7]. In [8], Riva et al., have detailed the scope of affective computing and their applications in virtual reality. Chen et al., have developed a wearable affective robot in [9]. Suzuki et al., have also developed robots that can recognize and interpret human affects [10]. Once the emotion is recognized, the elicitation methods are mostly depended on immersive environments such as head mount displays including virtual reality (VR) headsets. To reduce the complexity, researchers have deployed haptic signals as feedback [11]. Haptics are simple vibration rhythms that can be used for alerting the user or conveying any message such as weather change of status of the sensors [12], and [13].

System-level modeling of such integrative systems involve challenges in identifying the right components, starting from a simple temperature sensor [15] to modeling all the aspects or components of the system-level design [16]. The current research drive is focussed on developing cost-effective and highly efficient systems using off-the-shelf components[17], [18].

V. System level modeling of Easy-Assist

A. *Features for monitoring human affects*

The focus of this research is to find a correlation between human state and emotion in an IoT-based framework. The inputs to this state and emotion recognition framework are obtained using both the Easy-Assist wearable and face recognition using camera. The features identified for building this affective framework are accelerometer values, pulse rate variability, and face recognition. Using these features, the proposed state and emotion recognition algorithm is built by classifying these inputs into 5 identified states and 4 emotions.

B. Proposed Fall Detection Algorithm

The proposed fall detection algorithm is given in figure 3. The Easy-Assist activity monitoring algorithm acquires pulse rate and accelerometer values from high sensitivity pulse oximeter and heart rate sensor and highly accurate accelerometer which are used in the custom-built wearable. The pulse oximeter biosensor uses LED reflective solution to measure the person's heart rate and pulse. After acquiring the sensor values, the value of g and pulse rate are recorded along with the timestamp. This value is considered as a reference and the sensor values are constantly recorded. Whenever there is an activity detected, there is a change in the accelerometer sensor value and pulse oximeter value. This change in value is recorded as "current" value. Whenever there is a change in the value, the variability in the sensor values is analyzed with respect to time. If there is a rapid change in the values, the

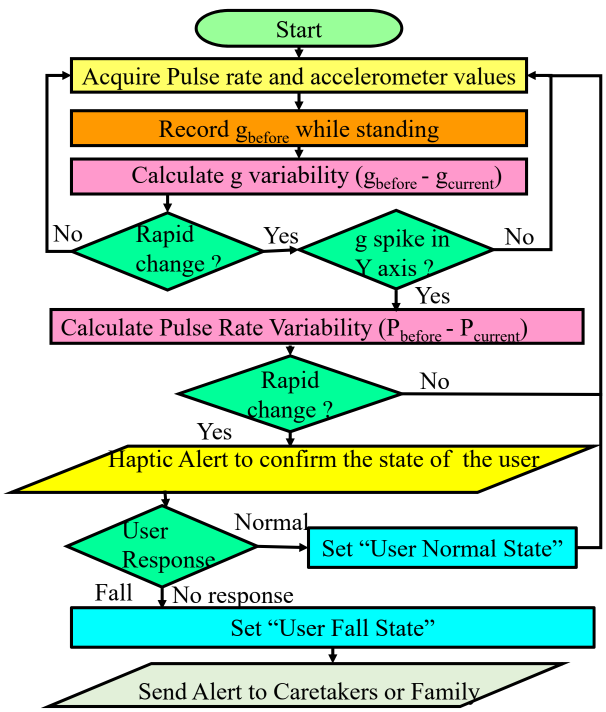


Fig. 3. Proposed Fall Detection Algorithm

user is given a haptic alert, to confirm the state of the user. This is to identify if the user is in normal state or fall state. Depending upon the user response obtained, the reference sensor values are obtained. i.e. if the user confirms that they are in their normal state, then the reference values for both the pulse oximeter and accelerometer values are updated. And if either the user confirms that they have fallen down or there is no response from the user, then the caretakers and identified family members are alerted immediately. This list of identified family members along with the name of the caretakers are obtained from the user before deploying the wearable.

C. Proposed Easy-Assist State and Emotion Detection Algorithm

Generally, in the affective monitoring research, the emotion recognition algorithms are built using visual or speech features clubbed with monitoring the brain waves by using electroencephalogram (EEG) and/or electrocardiogram (ECG or EKG). For the ease of monitoring affective states on a daily basis, we propose a state and emotion detection algorithm using wearable, and visual features i.e. face detection and recognition using video processing.

With identified features, 5 states and 4 emotions are to be recognized. The state of the user is primarily derived using the custom-built wearable whereas the emotion of the person is recognized and interpreted using an advanced face detection algorithm built with help of vision accelerator attached to a single board computer. With the help of the vision accelerator, training the machine to perform face detection and recognition becomes easier. The features from the wearable and identified facial expressions are labelled as one of the 5 states or 4 emotions.

The proposed easy-assist state and emotion recognition algorithm is built by training a multi-class supervised algorithm based on support vector machines. The objective of this algorithm is to identify a correlation between the identified states and emotion and establish and group them into 3 final classes: Normal, Active, Alert. The proposed methodology followed to group the 5 state classes and 4 emotion classes into 3 final Easy-Assist classes is given in Table I. It should be noted that the alert class includes both haptic alert and alerting the caretakers and family, depending upon the severity of the state. i.e. if the user is in Annoyed and fall state, then the help needs to arrive in addition to helping with the haptic alert whereas if the person is in annoyed and stand state, then a haptic alert to help them remain in the normal state would suffice.

TABLE I
METHODOLOGY TO GROUP STATES AND EMOTIONS TO DERIVE EASY-ASSIST STATE AND EMOTION DETECTION ALGORITHM

Active / Emotion	Stand	Sit	Laying	Walking	Fall
Normal	Active	Normal	Normal	Active	Alert
Happy	Active	Normal	Normal	Active	Alert
Panic	Alert	Alert	Alert	Alert	Alert
Annoyed	Alert	Alert	Alert	Alert	Alert

D. Proposed Easy-Assist Emotion Elicitation Methodology

In the affective framework, it is important to identify methodologies to give feedback to the user which can help in eliciting the user's emotions. For example if the user seems annoyed or sad, it is important to help them stay in their normal state by using some feedback system. In the easy-assist framework, if the user is in panic or annoyed state of emotion coupled with a detected fall, it is important to help them stay in normal or happy states to encourage them to come back to normal state. This change of emotional states can be achieved using audio or feedback systems. In this research, we propose a haptic-based feedback system that helps the user to revert to their normal state.

VI. Implementation and Validation of Easy-Assist

The implementation of the proposed framework is done with the help of off-the shelf components, with an aim to achieve low-cost, low-power, high-efficient IoT-based framework.

A. Easy-Assist Wearable

The easy-assist wearable helps in obtaining accelerometer and pulse oximeter values and provides a haptic alert to the user as and when required. Figure 4 shows the custom-built wearable designed using the off-the-shelf components along with the list of the components used to design the prototype.

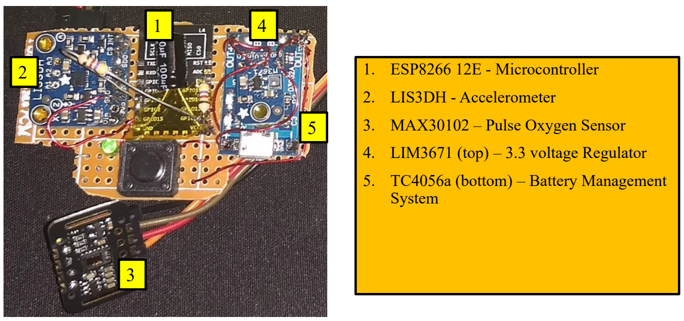


Fig. 4. Proposed Custom-built Easy-Assist Wearable prototype using Commercially available off-the shelf components

With an aim to achieve a cost-effective wearable, thorough research on available off-the-shelf sensors and controllers was done before building the current wearable. Each of the 5 main components used in the easy-assist wearable design was analyzed and multiple trial runs were done before using the component in the wearable design. In addition to the sensors shown in the figure, a vibration sensor is used at the back of the wearable, which helps in playing advance haptic patterns as feedback to the user.

The ESP8266 12e is a single-chip device that is a low-cost Wi-Fi enabled microchip that helps in achieving microcontroller stability along with full TCP/IP stack. The core of the wearable sensing system contains 2 main sensors:an off-the-shelf low-power 3-axis accelerometer sensor, LIS3dh, for sensing 3 axis sensing with a scaling of up to 16g and low-power highly accurate heart rate and pulse oximeter sensor, MAX30102. The power budget of the developed wearable is ideal for mobile real-time monitoring as well as long term data logging. To deploy it in the real-time application as a wearable, the prototype was powered using a single-cell lithium chip, TC4056a. This battery management system operates in 4.5-5.5 V. To minimize the overall power budget and extend the battery life, a 3.3 Voltage regulator, LIM3671 was deployed.

The data obtained from the Easy-Assist wearable is transmitted wirelessly to the IoT cloud. Figure 5 shows the working prototype of the developed Easy-Assist wearable. Figure 5 (a) shows the dimensions of the proposed prototype that can be easily placed on the wrist. Figure 5 (b) shows the working prototype with the base of the wearable, IoT controller as laptop. The data obtained using the wearable are further labelled into 5 state classes. As seen in the figure, the latency in detecting the state of the user i.e., if fall is detected and there is no pulse, was in the order of few milliseconds (200-350 ms).

B. Validation of Affective Framework

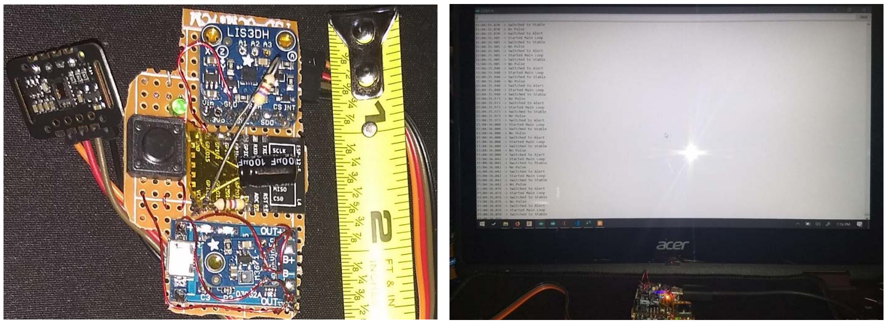
The emotion recognition framework was implemented using Intel Movidus Neural Computing Stick (NCS 2) to Raspberry Pi 3+. This framework was used for 2 main applications: 1. build a facial expression detection network that can recognize the emotions of the user and classify into 4 main emotional states. 2. Validate the fall state of the user as detected through the Easy-Assist wearable. The emotion classification dataset obtained using the Raspberry Pi 3+ and Intel Movidus NCS 2 are transmitted to the IoT cloud where further big data and deep learning algorithms are deployed to build a stronger network. Due to the multi-dimensionality nature of the data obtained through the wearable and face expression detection, a multi-class SVM model was built using the Classification Learner App of MATLAB®, after careful evaluation of other learning models. The total size of the dataset was 21,700 with 9400 data points in normal class, 5500 in active class and 6800 in Alert class. The model was trained with 70% of the data and tested with 30% of the data. Figure 6 shows the confusion matrix of the true and predicted class. The total testing data for each of the classes were 2820 for normal class, 1650 for active class and 2040 for alert class. In the figure, TPR indicates true positive and FNR indicates False Negatives.

TABLE II
Characterization Table of the Proposed Affective Framework

Sensing Platform	Custom-built Easy-Assist wearable
Emotion Detection	Raspberry Pi 3+, Intel Movidus Bar
Emotion Elicitation	Haptic Alert
Cloud	IoT Cloud
Machine Learning (ML) Evaluation	MATLAB® Learning App
ML model	Multi-class SVM model
Cross-validation	10-fold

VII. Conclusions and Future Research

This research focussed on developing an intelligent haptic-based framework using advance computing fields such as affective computing and Internet of Things. The proposed research included design of efficient hardware prototype, Easy-Assist wearable along with the emotion detection framework based on Raspberry Pi 3+. The proposed research was evaluated using the dataset obtained from the proposed framework with latency in few orders of milliseconds. Future directions of this research involve deploying the easy-assist framework in a fully automated environment with robots that can help seniors to live their retirement years at ease. The proposed framework can be deployed for multiple applications in addition to fall detection. Additionally, the use of fully immersive



(a) (b)

Fig. 5. Custom-built Easy-Assist Wearable prototype. (a) Easy-Assist prototype along with measurements (b) Easy-Assist prototype connected to a Laptop acting as base

Fig. 6. Confusion matrix of multiclass activity classification using state and emotion features extracted from Easy-Assist framework by multi-class SVM at cross-validation.

environments such as head mount displays and virtual reality headsets are to be investigated for this application.

VIII. Acknowledgement

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References

[1] M. Uddin, W. Khasksar, and J. Torrensen, "Ambient sensors for elderly care and independent living: A survey," *Sensors*, vol. 18, no. 7, 2018.

[2] P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. K. Ganapathiraju, "Everything you wanted to know about smart health care: Evaluating the different technologies and components of the internet of things for better health," *IEEE Consumer Electronics Magazine*, vol. 7, no. 1, pp. 18–28, Jan. 2018.

[3] S. P. Mohanty, U. Choppali, and E. Kougianos, "Everything You wanted to Know about Smart Cities," *IEEE Consumer Electronics Magazine*, vol. 5, no. 3, pp. 60–70, July 2016.

[4] R. W. Picard, "Affective computing," 1997.

[5] K. K. B. Peetoom, M. A. S. Lexis, M. Joore, C. D. Dirksen, and L. P. D. Witte, "Literature review on monitoring technologies and their outcomes in independently living elderly people," *Disability and Rehabilitation: Assistive Technology*, vol. 10, no. 4, pp. 271–294, 2015. [Online]. Available: https://doi.org/10.3109/17483107.2014.961179

[6] E. Vyas and R. P. W, "Affective pattern classification," *Emotional and Intelligent: The Tangled Knot of Cognition*, vol. 176182, 1998.

[7] J. Martin-Morales, J. L. Higuera-Trujillo, A. Greco, J. Guixeres, C. Llinares, E. P. Scilingo, M. Alcañiz, and G. Valenza, "Affective computing in virtual reality: Emotion recognition from brain and heartbeat dynamics using wearable sensors," *Scientific Reports*, vol. 8, no. 1, 2018.

[8] G. Riva, F. Mantovani, C. S. Capideville, A. Preziosa, F. Morganti, D. Villani, A. Gaggioli, C. Botella, and M. Alcañiz, "Affective interactions using virtual reality: the link between presence and emotions," *CyberPsychology & Behavior*, vol. 10, no. 1, pp. 45–56, 2007.

[9] M. Chen, J. Zhou, G. Tao, J. Yang, and L. Hu, "Wearable affective robot," *IEEE Access*, vol. 6, pp. 64 766–64 776, 2018.

[10] K. Suzuki, A. Gruebler, and V. Berenz, "Coaching robots with biosignals based on human affective social behaviors," in *8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 2013, p. 419.

[11] R. Jacob, B. Shalaik, A. C. Winstanley, and P. Mooney, "Haptic feedback for passengers using public transport," in *International Conference on Digital Information and Communication Technology and Its Applications*, 2011, pp. 24–32.

[12] X. Fu and D. Li, "Haptic shoes: representing information by vibration," in *proceedings of the 2005 Asia-Pacific symposium on Information visualisation-Volume 45*, 2005, pp. 47–50.

[13] S. Töyssy, J. Raisamo, and R. Raisamo, "Telling time by vibration," in *International Conference on Human Haptic Sensing and Touch Enabled Computer Applications*, 2008, pp. 924–929.

[14] J. Ryu, J. Jung, S. Kim, and S. Choi, "Perceptually transparent vibration rendering using a vibration motor for haptic interaction," in *RO-MAN 2007-The 16th IEEE International Symposium on Robot and Human Interactive Communication*, 2007, pp. 310–315.

[15] P. Sundaravadivel, S. P. Mohanty, E. Kougianos, and U. Albalawi, "An energy efficient sensor for thyroid monitoring through the iot," in *17th International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems (EuroSimE)*, 2016.

[16] P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty, and E. Kougianos, "Smart-log: A deep-learning based automated nutrition monitoring system in the iot," *IEEE Transactions on Consumer Electronics*, vol. 64, no. 3, pp. 390–398, 2018.

[17] P. Sundaravadivel, S. P. Mohanty, E. Kougianos, V. P. Yanambaka, and M. K. Ganapathiraju, "Smart-walk: An intelligent physiological monitoring system for smart families," in *IEEE International Conference on Consumer Electronics (ICCE)*, 2018, pp. 1–4.

[18] L. Rachakonda, P. Sundaravadivel, S. P. Mohanty, E. Kougianos, and M. Ganapathiraju, "A smart sensor in the iomt for stress level detection," in *IEEE International Symposium on Smart Electronic Systems (iSES)*, 2018, pp. 141–145.