IC-SAFE:Intelligent Connected Sensing Approaches for the Elderly

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***Abstract*—Senior citizens, young children, and people with age-related diseases, often find it hard to express themselves. They are not fully aware of their need for help, or how to ask for assistance. This lack of awareness decreases the quality of life, and even endangers those individuals.**

IC-SAFE (Intelligent Connected Sensing Approaches for the Elderly) tracks the safety of the elderly by using various connected smart wearable sensors. IC-SAFE collects motion data, including walking gaits, arm and leg tremors, and long lounging positions, from many lightweight body sensors to identify the safety status (both physical and emotional) of dementia patients. Feasibility tests have been performed using IMU (Inertial Measurement Unit) sensors in various positions and data from these experiments has been gathered. We have proposed efficient real-time algorithms using analytical learning methods and identified several safety target scenarios by analyzing the corresponding gait data.

I. Introduction

The norm of our societal life consists of various communication methods. However, senior citizens, young children, and people with age-related diseases often find it hard to express themselves. They are not fully aware of their need for help, especially when they are lost and wandering. Hence, loved ones cannot provide timely assistance. One of the most significant concerns is age-related diseases, such as dementia. Seven in ten people with dementia will wander. In such cases, these patients would need to obtain a full-time caretaker, move into an assisted living facility, or, worst case scenario, be locked up. These changes lead to a decrease in quality of life. Most of the existing recovery approaches assume that a few designated caregivers have complete responsibility for the patients 24/7, however, this is not always the case. In the event that a patient is not being watched, this could potentially put their life in danger should they end up in a life-threatening situation.

The primary objective of the IC-SAFE (Intelligent Connected Sensing Approaches for the Elderly) is to follow the safety of aging people by using various connected, intelligent wearable sensors. Dementia patients have been observed to perform certain actions, alluding to their need for assistance. IC-SAFE is able to identify these actions and alert a caretaker. In theory, an individual can recognize a lack of movement (a long idle status), the onset or aggression of tremors, and aggravated dementia due to depressive rumination as an issue. However, a patient suffering from dementia will not be able to appropriately express their needs to a caretaker in a timely fashion. As illustrated in Fig. 1, IC-SAFE consists of motion sensing, motion classification, and motion evaluation functions. IC-SAFE provides an automated and minimally invasive solution for sensing initial symptoms of distress by coordinating motion data, including walking gaits, arm and leg tremors and long lounging positions to classify the safety status of dementia patients, both physically and emotionally. Lastly, it alerts family members and caretakers about the situation before the symptoms foster into a further diagnosis. This paper identifies several scenarios for dementia patients, and proposes a few practical detection algorithms. It has been observed that patients with dementia perform certain repetitive motions, such as walking in a circle and sitting idle with their head bowed, in addition to the onset of other symptoms, such as aggravated tremors in the hands, knees, and ankles. We have accepted these motions as an indication of emotional or physical status change. We further characterized these actions into abnormal walking patterns and repetitive motions–specifically hand tremors and leg tremors. In order to eliminate false positives triggered by reading books, normal walking, and hand-writing, we have identified a threshold between similar actions, all of which have a high confidence rate. To collect this data, we harnessed IMU (Inertial Measurement Unit) sensors to various body locations and used WiFi and BLE communications for connecting sensors, in addition to employing smartphone-based mobile apps. With this data, we are proposing efficient, real-time algorithms for determining the emotional status, with accuracy and usability in mind.

Although the current IC-SAFE is a rudimentary experimentation prototype, eventually, IC-SAFE is motivated to target and automate an Alive Inside [1] application as a future product. As shown in Fig. 2, Alive Inside is a humanitarian project to revitalize the memory of senior citizens by playing cherished music of their youth (and memory). However, due to being a manual process, music cannot start playing automati-

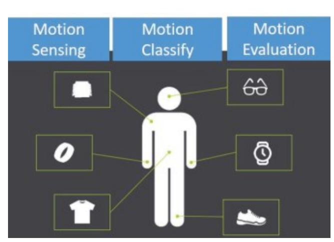

Fig. 1. Connected Smart Wearables

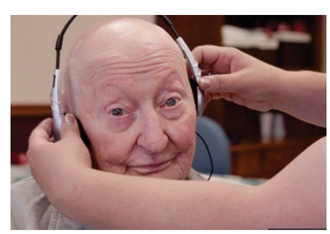

Fig. 2. Alive Inside Project [1]

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cally when needed. IC-SAFE would be able to automatically sense emotions and play the right music for the patient (the music selection itself is another area of research) via bone-conducting headphones or intelligent speakers such as Alexa, Google Assistant, and Siri.

The remainder of the paper is organized as follows: Section II discusses the related work. We describe the IC-SAFE system architecture and motion-sensing algorithms in Section III. The implementation and performance evaluation results are presented in Section IV. Finally, we conclude our work in Section V.

II. Related Work

In this section, we review various existing sensing methods and compare them with the proposed approach.

[6] studied data capture technologies for processing and decision support using a wide range of wearable devices and sensors, including accelerometers, gyroscopes, wireless communication networks, and power supplies. One of the authors' previous work [14] investigated the relationship between EEG signals and eye gazes to identify the electrodes and frequency bands suitable for measuring the mental state during learning. Many studies have been conducted to estimate emotions from EEGs. Wei et al. [17] performed emotion classification using DEAP dataset [12] and SEED dataset [9]. Acharya et al. [5] created an algorithm for diagnosing depression. The diagnosis accuracy was at a level that can be used as a second opinion. Ramy et al. [10] enabled predicting seizures in patients with epilepsy. [16] studied abnormal walking patterns, including slower speed walking with smaller steps and walking in a circle (walking around), which can be a potential indication of hesitance on body control and cognitive decision. [8] researched body sensors to detect many variables such as speed, distance, steps taken, floors climbed, and calories burned. [13] and [7] implemented a real-time waist-mounted tri-axial accelerometer unit to detect a range of essential daily activities, including walking and posture. [15] and [18] researched on monitoring blood oxygen saturation (SpO2), heart rates, and record hand posture while manipulating objects, such as eating or dressing. [11] measures body temperature through the use of an ear probe which detects infrared radiation from the tympanic membrane.

IC-SAFE approach is different from the existing work because it tracks the safety of the elderly by using various connected smart wearable sensors. IC-SAFE coordinates connected sensors to identify the safety status of dementia patients by collecting motion data, including walking gaits, arm and leg tremors, and long lounging positions, from many lightweight body sensors.

III. IC-SAFE Architecture and Algorithm

This section presents the architecture of IC-SAFE and describes implemented system components. Movement detection algorithms are also described in detail.

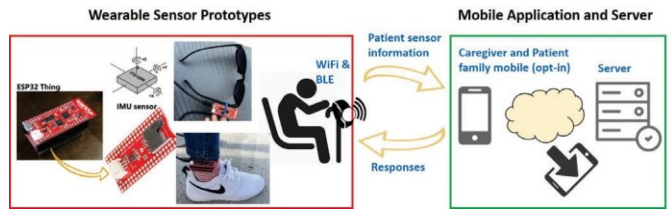

Fig. 3. IC-SAFE Architecture

A. IC-SAFE Architecture

As presented in Fig. 3, the IC-SAFE system consists of two functional entities, including wearable sensor prototypes for collecting gait data in addition to a mobile app, and an IC-SAFE server for analyzing the data and notifying alarms for both patients and their caregivers. The wearable sensors collect various patient gait data in real-time using an accelerometer and gyroscope. These perform an initial analysis, and then send the data to mobile apps for further complex processing. The sensors and the edge devices process the raw data as much as possible. When the target motions are detected, the sensor device sends them to the mobile application on the mobile device via WiFi or beacon (BLE) signal. Sensing algorithms process the data to identify the target movements. The mobile app then sends the safety notifications to an IC-SAFE server, and provides alerts and related information to the registered caregivers. When the sensors get a new signal, a mobile caregiver application receives alerts from the IC-SAFE server.

- **Wearable Sensor Prototypes:** We prototyped a sensor device using a SparkFun Esp32 Thing by harnessing an Inertial Measurement Unit (IMU) Motion Shield. The SparkFun ESP32 Thing is a development platform for Expresso ESP32. The ESP32 supports both WiFi and Bluetooth Low-Energy (BLE) communications. We use an IMU Motion Shield with onboard LSM9DS1 IMU to sense various movement patterns, measuring three fundamental movement properties: angular velocity, acceleration, and heading in a single IC. It produces nine pieces of data: acceleration in x/y/z, angular rotation in x/y/z, and magnetic force in x/y/z, which can measure a body's specific energy, angular rate, and the magnetic field surrounding the body, using a combination of accelerometers, gyroscopes, and magnetometers. Recent development allows for the production of IMU-enabled GPS devices. We implemented the movement detection algorithms embedded in the sensor device using the Arduino IDE. The programming languages used to implement them are C/C++ and Python.
- **Mobile Application and IC-SAFE Server:** A mobile application conveys alerts created by sensors to the IC-SAFE server and the respective caregivers. The application works as a bridge between the wearable sensors and the server. The app also sends alerts to the registered caregivers in multiple means, such as email or text messages, when any target motion level is identified. The IC-SAFE Server is implemented with a cloud-hosted Firebase database plat-

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form, offering various APIs for the application developers, including Android Studio and iOS, and JavaScript SDKs. It stores data in JSON format. Since we built a proof-of-concept system, we reserve patients' disease history information (not genuine), including the date, time, and patient's movement history collected from the sensor devices. The server also has caregivers' registration information under the identification of each patient. It periodically synchronizes patient and caregiver applications by checking the caregiver information in the database.

B. Abnormal Gait Detection Algorithms

The proposed IC-SAFE detection algorithms are designed for three representative motions of dementia patients.

- **Abnormal Walking Pattern Detection:** We identify abnormal walking patterns and their changes. Gait disorders are more prevalent in dementia patients than in healthy, aging individuals, and are related to cognitive dissolution. Dementia-related gait changes (DRGC) include smaller steps, slower speed, festination or shuffling, retropulsion, trouble turning, turning circles, etc. We classify smaller steps, slower pace, and walking in a circle (walking around repetitively) as gait-changes. We designed a detection algorithm by walking in a circle with an IMU sensor on an ankle. Fig. 4 shows both normal walking and smaller steps walking patterns observed from the accelerometer. Taking smaller steps shows more signals than normal walking in the same period. A walking cadence (steps/min) has been identified from the data. Although other research suggests reasonable heuristic walking cadence thresholds (100 and 130 steps/min for adults between 21 and 40 years old), [16], dementia declines walking cadence resulting in shorter strides [4]. However, since walking tempo depends on personal situations, those absolute values are not applicable. We identify and review the change in walking cadence to alert caregivers. Fig. 5 shows the principal axis data from the gyroscope when walking in a circle. The most notable difference is gyroscope rotation data and heading value. It shows that the heading value changes from 0 to 360 degrees.

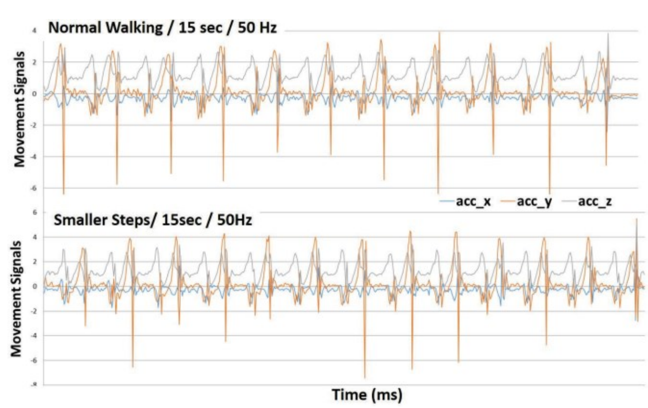

Fig. 4. Normal VS. Short Walking Patterns

Fig. 5. Walking in Circle

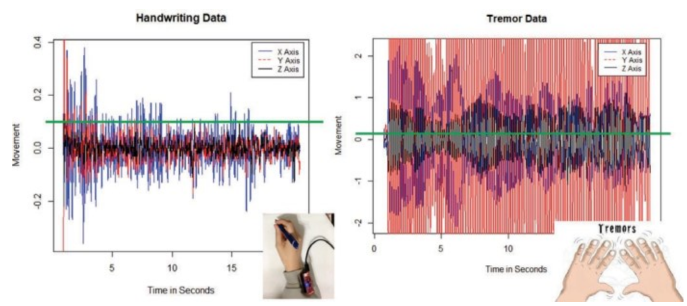

Fig. 6. Handwriting vs. Tremors

If the heading angular value changes from 0 to 360 and the accelerometer data pattern shows as Fig. 4 at the same time, we can consider the patient as wandering or needing help, indicating hesitance on body control and cognitive decision.

- **Tremors Detection:** We recognize tremors of the hand and leg, the most common tremor-related symptom of dementia patients. The tremor detection algorithm calculates signal values through time series, including counts, variations, frequencies, and strength levels for both hand and leg locations. For example, as shown in Figs. 6 and 7, regardless of the sensor location, tremor motions create a high volume of compact and consistent signal patterns. As different movement values are created according to the direction of the tremors and the sensor locations (either hand, knee, or ankle), we cannot rely on a single movement value. Hence, we use cumulative signal counts. Also, we distinguish the hand tremor from regular hand movements such as eating and writing motions and discern the leg tremors from normal walking or idling patterns. As illustrated in Figs. 6, the

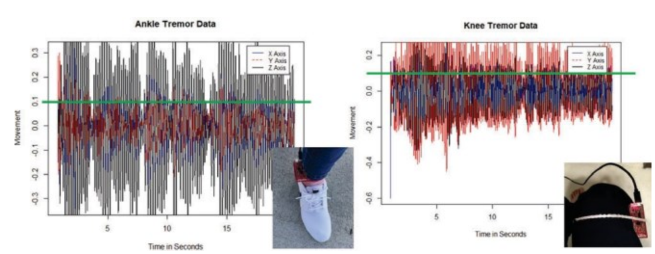

Fig. 7. Leg Tremors with Ankle vs. Knee Locations

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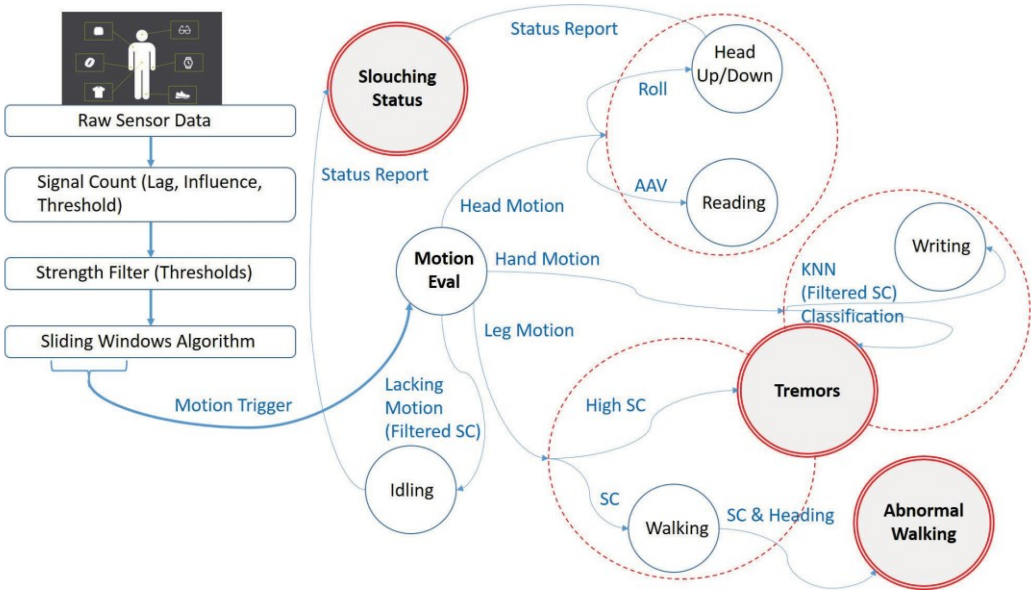

Fig. 8. IC-SAFE Algorithm

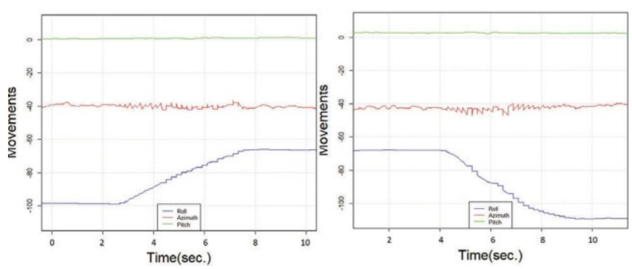

Fig. 9. Head Down vs. Head Up

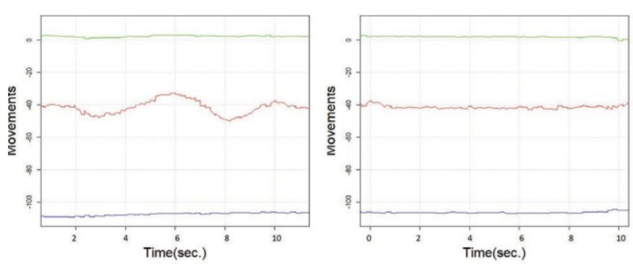

Fig. 10. Reading vs. Idling

handwriting motions create similar cumulative signal counts, and the signal pattern is consistent as well. The signal count alone cannot differentiate the handwriting from tremors. Hence, we use a filtered signal count by applying a strength filter to the signals with an adjustable threshold (e.g., 0.1 signal strength for all the movements). The same detection approach can differentiate the normal walking or idling patterns from the leg tremors.

- **Slouching Status Detection:** The lack of movement (long idling status) is one of the most common dementia symptoms. Many people with dementia suffer from physical problems and difficulties with movement (slow and stiff movements). They spend most of the time sitting in a chair. Although some people read the newspaper or take a nap, many are slouching in their chairs, which gradually deteriorates the cognitive ability of dementia patients. The general slouching motion is bowing the head to shoulder and maintaining the same pose for a long while. It is critical to intervene and encourage them to engage with others, while adjusting their posture.

We detected the lack of movement by designing a motion detection algorithm with the motion data from a sensor attached to a patient's eyeglass. The algorithm detects a change of the positional roll according to head movement. As shown in Fig. 10 on the right, if the head roll data remains the same (e.g., varying less than 3 degrees for mins.), the algorithm identifies the motion as an idling status. Specifically, we identify slouching posture in a chair and lowering heads still for an extended time. The algorithm catches up and down head motions, along with the idling status. As presented in Fig. 9, if the head roll data increases or decreases continuously in a direction for more than a certain threshold degree and time (e.g., changing more than 15 degrees for two sec.) after the idling status, it triggers the slouching status monitor. If the head roll data remains idle for a long time after the head-down movement, the algorithm identifies this as a slouching status. Also, the algorithm differentiates it from other similar actions, such as reading a newspaper. The head swings left and right slowly and slightly while reading. The angular velocity of a rotating object is the rate at which the angular coordinate changes for time. As shown in Fig. 10 on the left, the azimuth angle data makes a more significant angular coordinate change (by

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calculating an Average Angular Velocity (AAV)) than other idling actions or head movements.

Fig. 8 describes a combined process of the proposed IC-SAFE algorithm. The main objective of the algorithm is to detect the slouching status, tremors, and abnormal walking patterns in a timely fashion for protecting the elderly. It uses the raw sensor data (IMU data) from various wearable connected sensors as illustrated in Fig. 11. A signal count algorithm [3] is used for detecting cumulative Signal Counts (SC). It takes three configuration parameters, including the lag of the moving window for smoothing and adaption, the influence of signals on the detection threshold (mean and standard deviation), and the threshold of the signal classification based on standard deviation. We apply a signal strength filter to the generated signals for calculating the filtered SC. The strength filter normalizes the difference among people, sensor locations, and various motions (e.g., handwriting vs. tremors) with the adjustable threshold. The motion evaluation process is triggered using the sliding windows algorithm in time series. If there is little motion according to the filtered SC, the period is assigned an idling status, and then reports a slouching status. The motion classification initially starts with the sensor locations, including head, hand, and leg motions. The head motion class triggers the azimuth angle measurement by calculating an AAV to detect a reading motion that has a higher AAV than other idling or head movements. It also monitors the roll value to detect head movements up and down. This stage then records the status to identify a slouch. Eventually, it catches a slouching status using the sequence of status reports (e.g., idling + head down + idling or many consecutive idling status reports). The hand motion class triggers the filtered SC measurement to detect tremors and handwriting motion. If the filtered SC is high, it concurs a tremors status. Otherwise, it is considered as a handwriting status. The leg motion class triggers the SC measurement to detect tremors and walking motion. If the SC is high, it concurs a tremors status. Otherwise, it is considered as a regular walking status. It further analyzes the SC and heading values to detect abnormal walking situations, including short steps and circle walking.

IV. Evaluations

In this section, we present the experimental results of the feasibility tests of the proposed IC-SAFE detection algorithms.

A. Experimental setting

As shown in Fig. 11 (F), existing gait analyses have been conducted typically in a lab by attaching multiple sophisticated sensors on different parts of the body. Although this measures detailed and accurate body motions, it is not usable in practice. Our objective is to build a practical and cost-effective wearable sensor system by connecting a few sensors to detect various movements. We evaluated the proposed algorithms, including abnormal walking patterns, hand tremors, leg tremors, and the lack of movement using various motion data. We collected the motion data from 20 different people, including 12 males, 12 females, 3 transgender people, and 3 non-binary individuals. Their age range was from 13 to 90 (10 people between 13-30, 10 people between 31-60, and 10 people between 61-90). All age ranges are evenly distributed between each group of tests. We controlled the sensor locations and orientations but did not control how the actions were performed– each individual was told to perform the action as they normally would. We have conducted each set of experiments repetitively (10 times) for 10 to 15 seconds.

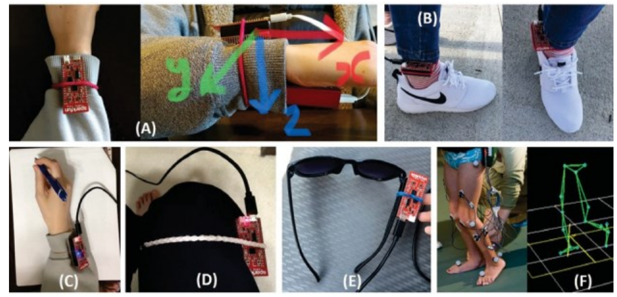

Fig. 11. Testing Scenarios of Wearable Sensors

We have attached a sensor device on the ankle (Fig. 11 (B)) for testing abnormal walking patterns and leg tremors. We have emulated several walking practices, including slow, average, and fast speeds, smaller steps, and wandering. We have also emulated diverse leg movement patterns by raising a leg up, down, left, and right, with both ground-fixed and unfixed leg positions. In addition, we examined the same leg movement test sets by attaching the sensor device on the knee (Fig. 11 (D)). To test hand tremors, we attached a sensor device on the wrist (Fig. 11 (A)) . We emulated diverse hand movement patterns by shaking hands up, down, right, and left, with both bent and straight arm positions. We also examined the handwriting movement (Fig. 11 (C)) to distinguish this action from tremors. We harnessed a sensor device on eyeglasses (Fig. 11 (E)) for testing the slouching status and lack of movement. We emulated diverse scenarios by changing head positions, reading newspapers, and lounging in a chair for an extended period of time.

B. Experimental Results of Detection Accuracy

To evaluate the tremor detection algorithm, as illustrated in Fig. 13, we assess the average number of filtered SC picked

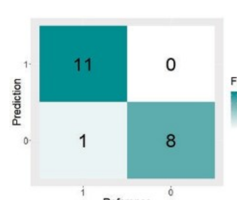

Fig. 12. Tremors vs. Writing Classification Accuracy

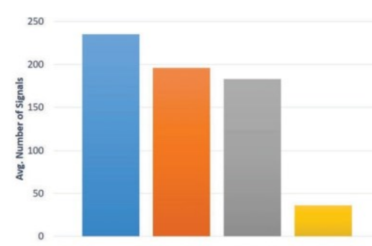

Fig. 13. Avg. Filtered SC

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up by the sensors on different locations, including hands, knees, and ankles, as well as the motions of handwriting. The filtered SC (with 0.1 signal filter) can distinguish tremor-related motions from handwriting-related motions. However, to normalize the difference between people, we use the K-Nearest Neighbors (KNN) classification algorithm instead of a threshold-based approach. We also conducted a classification accuracy test. We used the R language to perform the KNN classification algorithm. First, we built a data frame of 40 observations with two variables (a filtered SC and a factor of tremor or writing). We randomly separate the data into 20 training observations and 20 testing observations. Then, we performed a KNN prediction with K=3 by bootstrapping 1000 samples. We loaded a Caret package [2] for computing the confusion matrix. The confusion matrix in Fig. 12 shows that the prediction accuracy is 0.95.

C. Experimental Results of Slouching Status

To evaluate the slouching status detection algorithm, as illustrated in Fig. 14, we conducted movement scenarios in a particular sequence (idle, head down, idle, reading, idle, head up, read, and idle) using a sensor device on eyeglasses (Fig. 11 (E)). The algorithm pointed out each status correctly. For example, a head-down motion was detected at 20 seconds, and a head-up motion was detected at 53 seconds by monitoring the roll value in the green circle in Fig. 14. We also exploited the book reading motion detection to check if the algorithm could differentiate the motion of reading from other idle and head up/down motions. By tracking the azimuth angle value in the red circle in Fig. 14, it can catch a swing pattern, which periodically moves the head from left to right. The calculated AAV of a reading motion is much higher than other motions. Eventually, the algorithm detected a slouching status. Lastly, the algorithm was able to identify a sequence of motions, such as idle, head down, and idle after identifying a slouching status at 29 seconds in Fig. 14.

V. Conclusions

We introduced the IC-SAFE (Intelligent Connected Sensing Approaches for the Elderly) approach to tracking the safety of senior citizens by using various connected smart wearable sensors. To identify the physical and mental safety status of dementia patients, we proposed motion data coordination algorithms to detect the walking gaits, arm and leg tremors, and lounging positions for extended periods of time. We developed wearable IMU (Inertial Measurement Unit) sensor prototypes for various body positions and performed feasibility tests using the gathered data from field experiments. The results show that IC-SAFE can detect telling actions of distress and emotional transition scenarios in real-time and distinguish these actions from ordinary gaits with 95% accuracy.

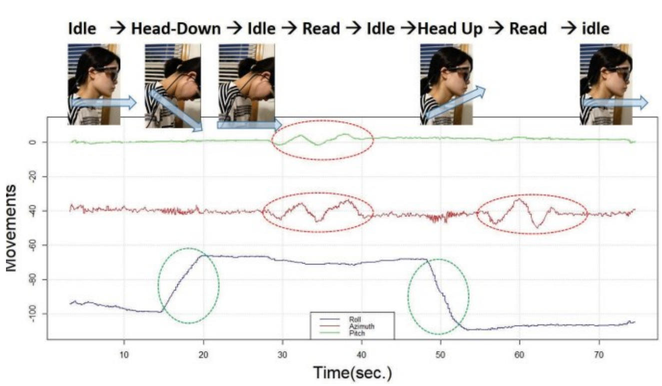

Fig. 14. Idle, Head down/up, and Reading Scenarios

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