

A Wearable System for Continuous Monitoring and Assessment of Speech, Gait, and Cognitive Decline for Early Diagnosis of ADRD

James Dieffenderfer, Alec Brewer*, Maxwell A. Noonan*, Madeline Smith, Emily Eichenlaub, Katarina L. Haley, Adam Jacks, Edgar Lobaton, Shevaun D. Neupert, Thomas M. Hess, Jason R. Franz, Sujit K. Ghosh, Veena Misra, Alper Bozkurt, *Senior Member, IEEE*

Abstract— Early detection of cognitive decline is essential to study mild cognitive impairment and Alzheimer’s Disease in order to develop targeted interventions and prevent or stop the progression of dementia. This requires continuous and longitudinal assessment and tracking of the related physiological and behavioral changes during daily life. In this paper, we present a low cost and low power wearable system custom designed to track the trends in speech, gait, and cognitive stress while also considering the important human factor needs such as privacy and compliance. In the form factors of a wristband and waist-patch, this multimodal, multi-sensor system measures inertial signals, sound, heart rate, electrodermal activity and pulse transit time. A total power consumption of 2.6 mW without any duty cycling allows for more than 3 weeks of run time between charges when 1500 mAh batteries are used.

Clinical Relevance— Much earlier detection of Alzheimer’s disease and related dementias may be possible by continuous monitoring of physiological and behavioral state using application specific wearable sensors during the activities of daily life.

I. INTRODUCTION

Alzheimer’s disease and related dementias (ADRD) are growing global concerns with significant negative psychological, social, and economic impact, not only for the patients but also their caregivers and social circles. These health issues are often characterized by a progressing cognitive decline that is reflected over other activities of daily life such as gait and speech. The current methods used for quantification of cognitive decline are based on expert observation in clinics through a battery of cognitive tests. This temporary and focused assessment may miss critical longitudinal day-to-day variations. Being in a laboratory environment or interacting with a medical professional may also obscure the symptoms. There is a need to generate continuous and longitudinal data to let the new developments in artificial intelligence and big-data analysis to explore features that predict the onset of ADRD especially during relatively complex dual activities of life such as problem solving while talking, or talking while walking.

In current clinical ADRD assessment, patients’ cognitive abilities, such as concentration, memory, and problem solving are evaluated through a number of surveys and tests. In parallel, their spatial awareness, motor function and language skills are also recorded and evaluated. These are based on

expert observations and scoring, causing the assessment to be infrequent, invasive, subjective and costly. More recently, biomedical instrumentation has been used during these tests to collect quantitative data, for example, by measuring electroencephalography, heart rate variability, electrodermal activity, and inertial signals. There has been an emerging interest in recording these signals outside the lab environment and during the activities of daily life for passive, longitudinal and continuous assessment of behavioral or physiological decline. However, these efforts face important human factors barriers such as user compliance to use these sensors all the time and concerns related to privacy.

Recent developments in wearables allow the recording of some of the related parameters such as voice or body movement. The higher power consumption of these devices require a need for daily charging of the batteries which may cause compliance issues especially for a user population potentially being challenged by decreased memory function. Users of these devices may also find the recording of their speech as concerning for their privacy and confidentiality. Most of the available devices provide only a limited number of sensors and are deployed generally only on the wrist region. Therefore, early detection of ADRD needs new, cost effective, user friendly, wear-and-ignore wearable devices that can passively, longitudinally, and continuously generate data for simultaneous assessment of speech impairment, gait decline and cognitive stress during daily life activities.

Our team’s earlier work focused on the effect on aging in speech, gait, and cognitive analysis using data collected during clinical tests [1][8][14-18]. This paper reports our preliminary effort to present a one-of-a-kind application specific wearable system to move these assessments outside lab environments (Fig.1). This custom designed system records physiological and behavioral signals related to speech, gait, and cognitive stress continuously and longitudinally using multiple sensors and two body locations (wrist and waist). These include sound, inertial measurements, heart rate variability, pulse transit time, and electrodermal activity. This paper focuses on the hardware design processes, where the future work will look at the data collected with these devices in real-life environments, and perform an artificial intelligence based machine-learning analysis on the data for early detection of ADRD.

This work was supported by NSF under IIS-1915599, IIS-2037328, and EEC-1160483 (ERC ASSIST) and by NIH NICHD108473. The Talkbank Pitt corpus was supported by NIH NIAAG03705, NIAAG05133, and the blood pressure data by NIH NIA AG005552 (healthy controls) and NIA AG005552-28S1 (ADRD participants). *Equal contribution. (corresponding author: Alper Bozkurt, phone: 919-515-7349; e-mail: aybozkur@ncsu.edu)

J. Dieffenderfer, M.A. Noonan, A. Brewer, M. Smith, E. Lobaton, S.D. Neupert, T.M. Hess, S. Ghosh, V. Misra, and A. Bozkurt are with NC State University, Raleigh, NC 27695, USA. K.L. Haley and A. Jacks, are with the University of North Carolina (UNC) at Chapel Hill, Chapel Hill, NC 27599, USA. J. Franz and E. Eichenlaub are jointly affiliated with both UNC Chapel Hill and NC State University.

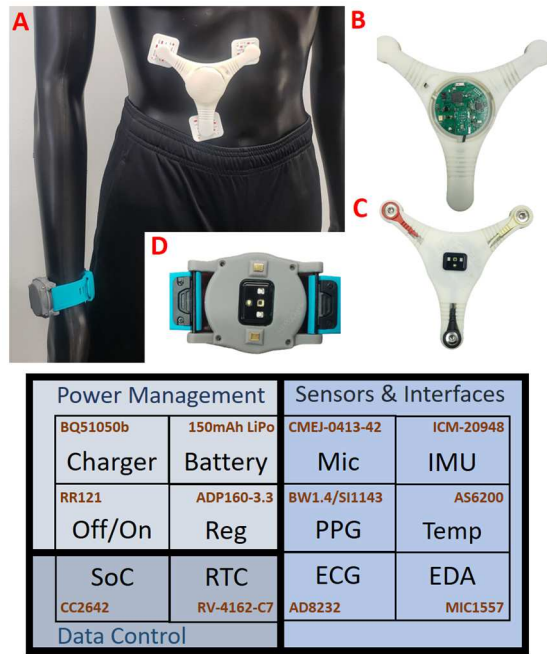


Figure 1: (A) The application specific custom designed wearable physiological and behavioral monitoring system for early detection of ADRD consisting of a (B-C) waist-patch and (D) wristband. (Bottom) System block diagram for both systems containing three subsystems with the integrated circuits used in each (indicated in brown font). ECG sensor is only on the waistband and the EDA on the wristband with all the other parts all common for both.

II. MATERIALS AND METHODS

A. System Design Process

We performed three analyses to support the design decisions for our system. The human studies were approved by the NC State or UNC-Chapel Hill Institutional Review Board.

1) Cognitive Stress

Electrodermal activity (EDA) is a well-known indicator of cognitive stress and included in the system. The pulse transit time is a parameter known to be correlated to blood pressure [2] and we performed an analysis of experimental data we collected to indicate the blood pressure difference between normal and cognitively impaired participants (age 61–85) who were either diagnosed with a cognitive impairment such as dementia or failed the Short Blessed Orientation-Memory-Concentration Test with a score of 7 or higher [3]. Cognitively normal participants were eligible to participate if they passed the Short Blessed Orientation Memory Concentration test with a score below 7. Cognitively normal participants visited the lab once, while cognitively impaired participants visited the lab twice with approximately 6 months between each visit. At each lab visit, participants completed a computerized memory-scan task. As participants are required to sustain engagement throughout each level of the task, task difficulty increased as a result of expended resources. Engagement of cognitive resources requires the expenditure of cognitive effort, which can be indexed through systolic blood pressure [4]. While completing these tasks, cardiovascular responsivity was assessed using a continuous noninvasive arterial blood pressure device, CNAP Monitor 500 HD (CNSystems Medizintechnik AG, Graz, Austria). Participants completed

four levels of the 30-item memory scan task, and some other surveys while connected to the CNAP monitor.

2) Gait Detection

We performed a pilot experiment to gain preliminary insight into the effect of sensor location on acceleration signals during normal walking and walking with perturbations. We collected data from 20 younger (age 19-25) and 4 older adults (age 68-74) walking at their preferred overground speed (~ 1.3 m/s) on a dual-belt treadmill. The participants walked normally at that speed for two minutes and while responding to eight treadmill-induced slip perturbations per foot, delivered at the instant of heel-strike, designed to elicit instability [5]–[7]. During these, the 3D positions of retroreflective markers placed on participants' posterior sacrum ("waist") and both lateral humeri ("upper arms") and ulnar styloid processes ("wrists") were recorded using a 16-camera motion capture system. To emulate the signals from wearable accelerometers, we calculated the second time derivative of each position time series and calculated the vector magnitude from each 3D acceleration signal.

3) Voice Analysis: Conversation Pause Detection

In our earlier work, we demonstrated that reducing audio sampling rate to 750 Hz helps obfuscating users' speech and preserving their privacy when using a wearable device for detecting certain characteristics in voice such as coughing [8].

To test the potential of this sampling frequency on voice analysis for detecting changes in speech and language in ADRD, we completed speech and lexical analyses of speech samples from the TalkBank Pitt Corpus [9], [10]. We extracted samples from 30 participants with probable ADRD during an early stage of progression and 30 neurotypical participants matched for sex, age, and education. The speech sample task was to describe a line drawing ("the cookie theft picture") that is part of standardized aphasia assessment [11]. The audio-recorded monologue was low-pass filtered at 350 Hz to simulate a sampling rate of 750 Hz, then analyzed with a custom Praat [12] script to determine the proportion of these monologues that were composed of pauses.

B. System Overview

The developed application specific system comprised two devices to be worn on the wrist and the waist and to be in contact with the skin (Fig.1). Each containing a separate Bluetooth Low Energy (BLE) enabled system-on-chip (SoC), these two devices were wirelessly connected to a central data aggregator (the user's smartphone). Due to the potential variance in BLE packet timing, timestamps for all the collected data were taken internally for each device and transmitted to the data aggregator along with the raw data. Each device had an onboard real time clock for precise time keeping and synchronization. In parallel to the wireless enabled SoC, we implemented a secondary, low-power, central processing unit (CPU) to perform sensor measurements and aggregate these into an alternating buffer for power conservation on both devices. Upon filling this buffer, the primary CPU woke up and transferred this collected data to the connected central device using the onboard BLE radio. In a parallel implementation, a Secure-Digital (SD) memory card was included on-board to store the data locally until a BLE connection automatically established with the smartphone.

This system was designed to assess cognitive stress, detect gait at various speeds and stillness, and tracking frequency of silence within conversational speech as quantitative biomedical parameters related to ADRD as follows:

1) Cognitive Stress Sensing

The wrist-device included three sensors for EDA, photoplethysmography (PPG) and wrist skin temperature. The waist-device also comprised a PPG and waist skin temperature, in addition to three-electrode based electrocardiogram (ECG). Measurement of PPG and ECG simultaneously and at two different locations not only improved the motion-artifact immunity [13] but also allowed for the measurement of pulse-transit and pulse-arrival time which are associated with blood pressure and cognitive stress.

The EDA circuit was based on the integrated circuit MIC 1557 (Microchip Technology Inc., Chandler, AZ) which outputs an 8 kHz square wave signal. This signal was sent through the skin via a pair of silver plated electrodes and the attenuation was measured after passing through a second order low pass filter circuit. 8 kHz frequency was chosen to overcome the electrode-to-skin interface capacitance. The voltage was subsequently measured by the SoC.

The PPG measurement was implemented in two different ways. The first PPG system was designed using a proximity detector SI1143 (Silicon Labs, Austin, TX) driving an 850 nm LED and receiving the raw pulsed PPG signal with an embedded implementation of a sample and hold circuit. The second PPG system was based on the integrated circuit module BW1.4 (Valencell Inc. Raleigh, NC). This module came with an additional microcontroller with embedded software for extracting heart rate along with other optically and motion derived metrics including step counts, cadence, instantaneous caloric burn rate, and maximal oxygen consumption (VO₂ max) from the PPG signal.

A single lead three electrode ECG measurement was performed by the front-end circuit AD8232 (Analog Devices, Wilmington, MA). ECG circuit was connected to the external analog to digital converter AD7142 (TI, Dallas, TX).

The temperature sensor on the wrist was exposed to the environment and the one on the waist was under the garment. The differential analysis of these can be correlated with users' environmental conditions for a context aware sensing. The temperature measurement was performed using the integrated circuit AS6200C (AMS-OSRAM AG, Austria) located directly next to the EDA electrodes to allow for minimal distance to the skin.

The ECG, EDA and PPG were sampled at a rate of 100 Hz and skin temperature and PPG derived metrics at 10 Hz.

2) Gait Sensing

To assess the walking activity of the users, the inertial measurement units provided the motion activity of the wrist and waist for a differential assessment. An IMU device we generally use in our systems is ICM-20948 (InvenSense Inc., San Jose, CA) with signals sampled at a rate of 100 Hz.

3) Speech Sensing

To delineate participant speech from ambient speech for assessing fluency measures, a microphone was included both on the wrist and waist locations for a differential assessment

of the user's voice and sound of nearby people. We used a standard integrated circuit microphone, VM1000 (Vesper Inc. Boston, MA), and a lower sampling rate to avoid conversations to be intelligible for preserving the privacy of the users and confidentiality of the information. As a measure of fluency, we analyzed pause durations and frequency of speech and silence for talking over a certain duration (such as 1 minute). We optimized the sampling rate to be low enough to differentiate such fluency measures as the pauses and gaps in the conversation but not the conversation content.

4) Ergonomic Enclosure Design

The wristband was designed as a wearable band using standard interchangeable 26 mm silicone band styles (Fig.1). The waist is a body location where it is relatively easy to install devices without needing to undress. The waist-patch was designed to either be attached to the waist skin using medical grade double sided sticky tape or to be attached to a band placed around the waist depending on user preference. Three medical grade gel-electrodes were used to record ECG signals. To prevent moisture damage and the degradation associated with typical device usage, the printed circuit boards and electronics were sealed using medical grade epoxy. Qi compliant wireless charging was implemented using the integrated circuit BQ51050b (TI, Dallas, TX) and a custom-designed charging receptacle ensuring the optimal alignment of receiver and transmitter coils with minimal distance in-between. For waterproofing, a Hall-effect based magnetic on/off switch was included on the circuit. The charger case contained a magnet inside its top lid to turn off the device upon closing it during the charging process. This also acted as a resetting mechanism if the devices experienced an error on the embedded system code and needed a restart.

C. Data Acquisition

We designed an iOS app for a smartphone collecting data from both devices over BLE simultaneously. In compliance with iOS BLE protocol, the maximum number of payload bytes for a BLE message was 182 bytes. As our system collects data from multiple sensors, in order to maximize the amount of data within this number of bytes, only a single timestamp was included which represented the last time of the last data point in the array of data. Thanks to the samples having precise timing, the app could extrapolate the rest of the timestamps for a given packet. The aggregated data was saved on a Cloud service (iCloud) as CSV files.

D. Experimental Evaluation

The main objective of this first step in research was to show that simultaneous data collection could occur between the two wearable devices and data streams relevant to both gait, speech, and cognitive stress could be captured in a time synchronous methodology. We assembled a prototype system and ran a proof-of-concept study with a healthy subject to demonstrate functionality of the system. For this, we used a standard and basic dual-task (gait and speech) protocol. The protocol included the following steps: (1) One minute of sitting and resting on a chair, (2) sitting while telling the children's story "Cinderella", (3) walking on a treadmill at 1.7 m/s without talking, and (4) walking on a treadmill at 1.7 m/s while telling the "Cinderella" story. The subject wore our system and also was tethered to a gold standard biomedical instrumentation (Biopac) for PPG, ECG, and EDA recording.

III. RESULTS

A. Design Process Analyses Results

Our analysis of blood pressure measurements between a control (healthy) group, and a group of individuals with ADRD demonstrated some detectable changes (Fig.2). These graphs include our preliminary results looking at a first session performed as a baseline (Wave1) and a follow up session 6 months later (Wave2) for two of the ADRD participants. The trends of blood pressure over time are summarized by fitting a piecewise linear spline (top plots). Histograms capturing the changes in blood pressure were then computed from the splice values (bottom plots). As shown, there was a clear trend illustrating that the controls show higher changes in blood pressure initially and over the entire session on average, and the second largest change corresponds to the Wave1 participants. This shows a progression on blood pressure from healthy participants to participants with more advanced ADRD. Over the entire session (i.e., when taking the difference between knot3 and knot0), the healthy individuals demonstrated an increase in blood pressure while the Wave2 participants demonstrated an overall decrease in pressure. These results are preliminary but support theory-driven hypotheses that participants with more cognitive resources exert more cognitive effort for longer periods of time.

Our analysis of the TalkBank Pitt Corpus showed that percent pause time after 350 Hz low-pass filtering was highly correlated with percent pause time for the full signal (Fig.3). This encouraged us to design our embedded system to filter out the higher frequency content and lower the sampling rate of microphone outputs to preserve privacy and confidentiality, while keeping sufficient potential to use the data to differentiate a healthy user from a user with cognitive decline.

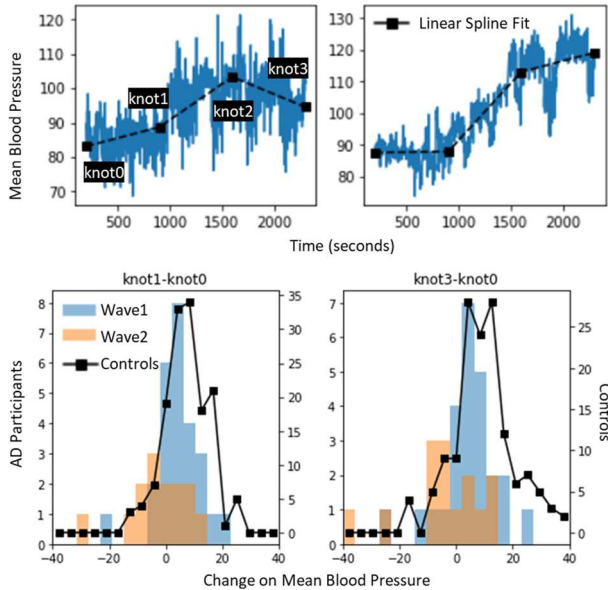


Figure 2: (Top) Illustration of the mean blood pressure data over time for two ADRD participants. The blue curve shows the raw measurements. The black line shows the piecewise linear spline fit on the data used to summarize the trends. (Bottom) Trends of the histograms of the changes in mean blood pressure over time. (Left) The trend on the first portion of the line spline fit (i.e., the difference between knot1 and knot0). (Right) The overall change in blood pressure from the start until the end of the session (i.e., the knot3 and knot0 difference).

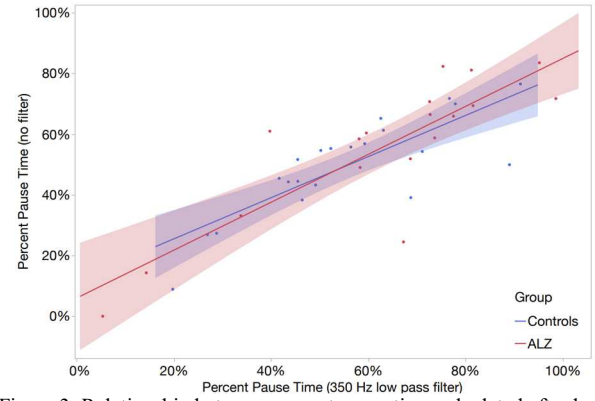


Figure 3: Relationship between percent pause time calculated after low-pass filtering at Nyquist frequency of 350 Hz (for 700 Hz) and from the unfiltered signal ($R^2 = 0.70$).

In terms of the most optimal location to detect walking activity, independent of age, we found the highest average and peak accelerations during normal walking at the wrist (Fig. 4C), each averaging roughly two-times larger than those measured at the waist (Fig. 4A). Wrist-worn sensors could also more effectively distinguish between-group differences in acceleration signals during normal walking; with peak and average wrist acceleration signals in older adults 28% and 38% higher than those in younger participants, respectively, compared to only 3% higher for both for a waist-worn sensor. Wrist accelerations also detected the largest change due to treadmill-induced slip perturbations, but only in young adults; peak and average contralateral wrist accelerations in younger adults were 91% and 36% higher than those measured during normal walking. Conversely, this early evidence suggests that a second (upper arm or waist) sensor may better detect age-related vulnerability to gait instability – at least that elicited by a slip. During perturbation responses, peak and average upper arm accelerations averaged 108% and 97% (perturbed side) and 81% and 51% (unperturbed side) higher in older adults than in younger adults, compared to only 54% and 33% (perturbed side) and 2% and 12% (unperturbed side) higher for a wrist-worn sensor, respectively. These results indicate the importance of a wrist sensor for walking detection, but with improvements in perturbation detection with the introduction of additional sensors on the waist or upper arm.

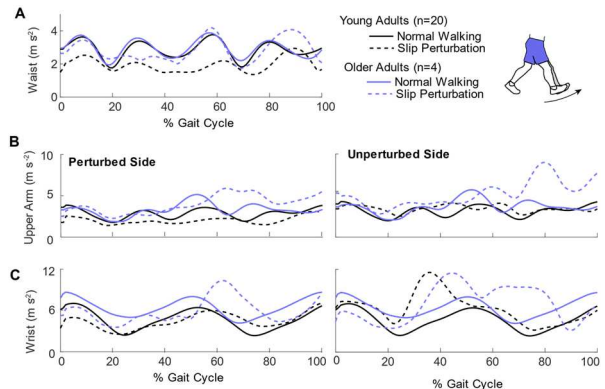


Figure 4: Acceleration vector magnitudes derived from markers on participants' "waist" (A), and upper arms (B), and wrists (C) plotted over an averaged gait cycle from heel-strike to heel-strike. Solid lines (Normal Walking) provide comparison to dashed lines derived from treadmill-induced slip perturbations. For both the perturbed and unperturbed, perturbation onset occurred at the instant of heel-strike (0%).

B. System Evaluation Results

The electronic power consumption analysis of the assembled system (Fig.1) demonstrated that the current draw for each device is heavily dependent on the sensor selection and can be optimized by duty cycling each sensor (Fig. 5). Even with relatively high throughput over BLE, the microcontroller power consumption often was a small percentage of the overall power consumption. The wristband had a total power consumption of 2.6 mW, which allows for more than 3 weeks of continuous usage with a 1500 mAh lithium-polymer (LiPo) battery. The waist node had a total power consumption of 2.5 mW, allowing a similar continual operation before needing a recharge. It should be noted that the system can be duty-cycled to extend the battery duration and put into sleep mode when the subjects are asleep. This can easily extend the battery duration to one year. The representative signal patterns of various sensors measured during the walking and talking test are provided in Figure 6. The microphones were able to provide audible speech files during both sitting and walking states. The audio files allow for the analysis of pitch, tempo, and quantity of pauses (among other speech metrics).

IV. FUTURE WORK AND CONCLUSIONS

This paper presented the design process and the first steps towards a novel, one-of-a-kind, wear-and-ignore, passive, and continuous monitoring system for a longitudinal multimodal data collection to develop algorithms for early detection of ADRD. Placed on the wrist and waist, the system can measure sound, inertial measurements, heart rate variability, pulse transit time, and electrodermal activity as behavioral and physiological indicators of gait and speech decline, and cognitive stress. The design process focused on lowering the sampling rate of the voice recording to preserve privacy and on lowering the power consumption to improve compliance by eliminating the need for frequent charging of the devices. The presented work here describes the hardware system design and demonstrates basic functionality. The future research will explore predictive artificial intelligence methods to use the data collected and the indices & metrics generated by the system for assessment of speech impairment, gait decline and cognitive stress for ADRD diagnosis and management.

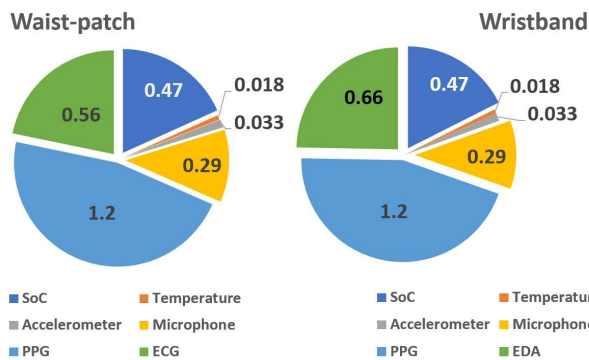


Figure 5: The distribution of power consumption for the waist-patch and the wristband. Each sensor can be duty cycled to extend the overall battery life.

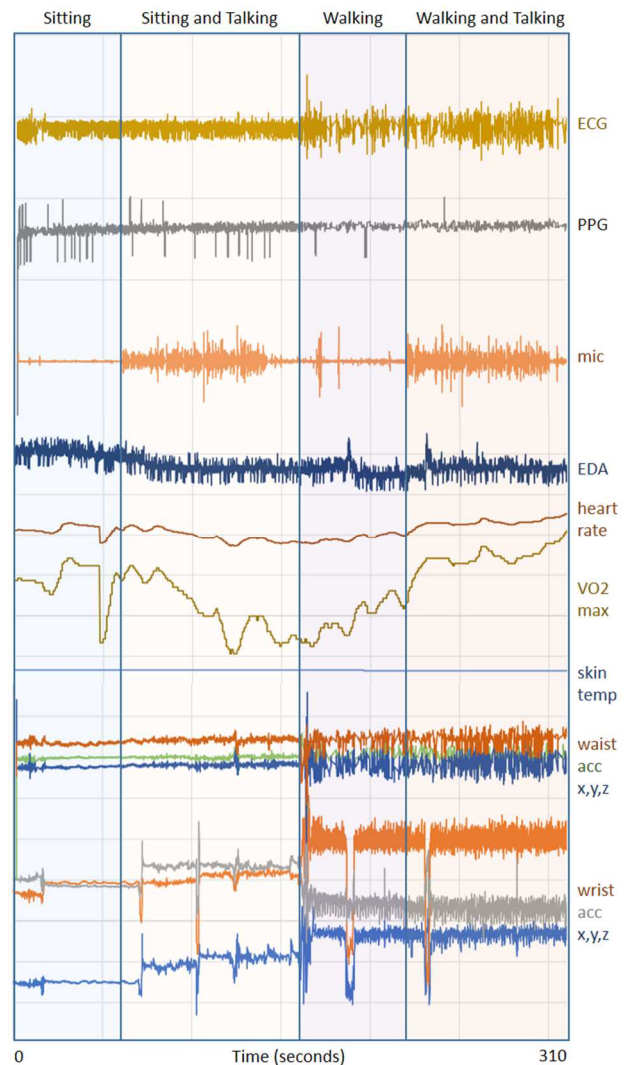


Figure 6: Representative data collected from the sensors during a walking and talking experiment to demonstrate the functionality of the system.

ACKNOWLEDGMENT

The authors would like to thank Soomin Kim for her help with the speech analysis.

REFERENCES

- [1] S. D. Neupert, C. M. Grownay, X. Zhu, J. K. Sorensen, E. L. Smith, and J. Hannig, "Bff: Bayesian, fiducial, and frequentist analysis of cognitive engagement among cognitively impaired older adults," *Entropy*, vol. 23, no. 4, 2021, doi: 10.3390/e23040428.
- [2] R. C. Block *et al.*, "Conventional pulse transit times as markers of blood pressure changes in humans," *Sci Rep*, vol. 10, no. 1, 2020, doi: 10.1038/s41598-020-73143-8.
- [3] R. Katzman, T. Brown, P. Fuld, A. Peck, R. Schechter, and H. Schimmel, "Validation of a short orientation-memory-concentration test of congestive

- impairment," *American Journal of Psychiatry*, vol. 140, no. 6, 1983, doi: 10.1176/ajp.140.6.734.
- [4] T. M. Hess, "Selective Engagement of Cognitive Resources: Motivational Influences on Older Adults' Cognitive Functioning," *Perspectives on Psychological Science*, vol. 9, no. 4, 2014, doi: 10.1177/1745691614527465.
- [5] A. Lee, T. Bhatt, and Y. C. Pai, "Generalization of treadmill perturbation to overground slip during gait: Effect of different perturbation distances on slip recovery," *J Biomech*, vol. 49, no. 2, 2016, doi: 10.1016/j.jbiomech.2015.11.021.
- [6] X. Liu, T. Bhatt, and Y. C. Pai, "Intensity and generalization of treadmill slip training: High or low, progressive increase or decrease?," *J Biomech*, vol. 49, no. 2, 2016, doi: 10.1016/j.jbiomech.2015.06.004.
- [7] J. Li and H. J. Huang, "Small directional treadmill perturbations induce differential gait stability adaptation," *J Neurophysiol*, vol. 127, no. 1, 2022, doi: 10.1152/jn.00091.2021.
- [8] M. Abdelkhalek, J. Qiu, M. Hernandez, A. Bozkurt, and E. Lobaton, "Investigating the Relationship between Cough Detection and Sampling Frequency for Wearable Devices," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2021. doi: 10.1109/EMBC46164.2021.9630082.
- [9] J. T. Becker, F. Boiler, O. L. Lopez, J. Saxton, and K. L. McGonigle, "The Natural History of Alzheimer's Disease: Description of Study Cohort and Accuracy of Diagnosis," *Arch Neurol*, vol. 51, no. 6, 1994, doi: 10.1001/archneur.1994.00540180063015.
- [10] F. Boller and J. Becker, "Dementiabank database guide," *University of Pittsburgh*, 2005.
- [11] H. Goodglass, E. Kaplan, and S. Weintraub, *BDAE: The Boston diagnostic aphasia examination*. Lippincott Williams & Wilkins Philadelphia, PA, 2001.
- [12] P. Boersma, D. Weenink, "Praat: Doing phonetics by computer (Version 6.0.31) [Computer Software]." 2017. [Online]. Available: <https://www.praat.org>
- [13] P. T. Gibbs, L. B. Wood, and H. H. Asada, "Active motion artifact cancellation for wearable health monitoring sensors using collocated MEMS accelerometers," in *Smart Structures and Materials 2005: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, 2005, vol. 5765. doi: 10.1117/12.600781.
- [14] K.L. Haley et al. "Speech metrics and samples that differentiate between nonfluent/agrammatic and logopenic variants of PPA," *Journal of Speech Language Hearing Research*, 64(3), 754-775, 2021. https://doi: 10.1044/2020_JSLHR-20-00445
- [15] R. Cavanaugh, K.L. Haley, "Subjective communication difficulties in very mild aphasia," *American Journal of Speech-Language Pathology*, 29(1S), 437-448, 2020.
- [16] V. Dubljević, S.D. Neupert, "The complex nature of willpower and conceptual mapping of its normative significance in research on stress, addiction, and dementia," *Behavioral and Brain Sciences*, 44, 2015.
- [17] J.R. Franz, "The age-associated reduction in propulsive power generation in walking," *Exercise and Sport Sciences Reviews*, 44(4), 129-136, 2016.
- [18] V. Misra, A. Bozkurt. Flexible technologies for self-powered wearable health and environmental sensing. *Proceedings of the IEEE*, 103(4), 665-681, 2015.