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Investigation into the Potential to Create a Force Myography-based Smart-home Controller for Aging Populations

Mona Lisa Delva, Maram Sakr, Rana Sadeghi Chegani, Mahta Khoshnam, and Carlo Menon, *Member, IEEE*

***Abstract*— Force Myography (FMG) quantifies the volumetric changes in a limb occurring with muscle contraction and can potentially be used to design convenient, low-cost interfaces to assist in activities of daily living (ADL). The aim of this study is to evaluate whether elders can effectively use an FMG-based wrist band to interact with their environment. In this regard, an FMG band consisted of an array of force-sensing resistors (FSRs) was designed. Ten participants were grouped in two classes, namely "senior" and "non-senior", and were instructed to perform control gestures and unconstrained ADL tasks while wearing the designed wrist band. To evaluate the usability of the band, correct identification of hand gestures and reaction times were noted. Results showed that seniors were capable of successfully performing a control gesture within 1.4 s of displaying the instruction during online testing. The individually-trained gesture identification algorithm achieved an accuracy of 76.5% in this case. Non-seniors had a reaction time of 0.9 s with an overall classification accuracy of 91.2%. This preliminary study demonstrates the potential and feasibility of utilizing FMG-based technology to provide elders with assistance during activities of daily living.**

I. Introduction

The increasing pace of population aging [1] has motivated research on developing technological solutions to provide elderly people with proper healthcare and to ensure that their quality of life is maintained with aging. Frequent visits to clinics and hospital stays are inconvenient for senior citizens, and create a potential strain on direct access to healthcare. Therefore, the concept of "aging in place" has been introduced to promote aging at home while maintaining the level of independence of seniors through developing supporting technologies [2], [3]. Remote monitoring systems and smart interfaces which facilitate interaction with different objects and assist with activities of daily living (ADL) are examples of such technologies [4].

Several technological solutions have been investigated and implemented to facilitate aging in place. Vision-based systems have been most commonly used to monitor posture for fall detections [5], to form smart-homes [6], to serve as emergency detection tools [7], and as device controls [8]. Vision-based systems are unobtrusive and easy to be concealed in the home environment, and can address challenges associated with deteriorating physical and mental capacities that affect technology adherence [9]. However, limitations such as illumination, occlusion, and potential overhead costs for real-time, accurate, and continuous monitoring hinder widespread application of these systems [10]. Moreover, concerns have been raised over privacy issues of such systems [11]. To address these concerns, silhouette-based and binary image systems which eliminate identifiable features and therefore, provide anonymity have been proposed [11], [12]. However, the data collected with these systems are not as comprehensive as those recorded by vision-based systems [11].

Voice and speech recognition techniques can be used to form stand-alone voice-based systems for applications such as control of peripheral devices, e.g., TV or radio, and requesting help through control of emergency response protocols [13]–[15]. They can also be used to enhance vision-based systems which is particularly valuable when cameras fail to detect or track movement. Effectiveness of voice-based systems can be maximized by implementing state of the art recognition and noise reduction software and using multiple microphones in the living space [15]–[17]. However, these systems are effective only if the user is able to generate proper commands [18], are obtrusive due to fact of having to talk to a house [19], and present barriers such as privacy concerns, confounding effects of ambient sounds and noises, and the lack of direct physical monitoring of the user.

This paper addresses the concern regarding independence of elderly people at home and focuses on developing a platform to control peripheral devices using force myography (FMG) techniques. In this approach, tactile sensors are used to track the volumetric changes in a limb resulting from underlying muscle activity. Measuring functional activity and limb kinematics have been shown to enhance the independence of seniors in ADL by providing a more comprehensive means to telemonitor users [20]. Although FMG-based technology has been successfully tested amongst young healthy populations [21], [22] and amputees [23] as well as for rehabilitation purposes [24], to the best of our knowledge, its potential as a communication platform for seniors has not yet been investigated.

Muscle activity information can be obtained using techniques such as accelerometer-based tracking of the position and orientation of upper extremities, electromyography (EMG) or force myography (FMG), and can be implemented in form of low-profile wearable devices [25]–[27]. Accelerometer-based techniques typically use inertial measurement units (IMUs) to monitor and promote physical activity, and can provide anonymized and direct user

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Authors are with Menrva Research Group, Schools of Mechatronic System and Engineering Science, Simon Fraser University, Metro Vancouver, BC, Canada (e-mail:{mld5, msakr, rchegani}@sfu.ca; mkhoshna@alumni.uwo.ca).

* Corresponding author: C. Menon (email: cmenon@sfu.ca; phone: 778-782-9338; fax: 778-782-7514).

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movement data, but are susceptible to artifacts such as noise, gyroscope drift, and magnetic field disturbances [28]. EMG-based techniques measure the electrical activity on the skin resulting from muscle contractions and are frequently used to non-invasively assess muscle activity. However, these measurements are not robust to external electrical interference and sweating, require precise sensor placement and/or extensive skin preparation, and are computationally demanding to process [29].

FMG-based techniques have gained momentum in innovative and novel device design due to their cost effectiveness, simple implementation, and potential to overcome the challenges typically faced when employing EMG-based techniques [30]–[32]. The aim of this study is to investigate whether seniors, considering their lower muscle tones [33], can successfully use an FMG-based platform to interact with a computer interface. In this regard, this study was conducted by assigning participants to one of two groups based on their age: non-senior (aged less than 60 years) and senior (aged greater than 60 years). While equipped with the custom FMG wrist band, participants were instructed to perform several gestures specifically chosen for peripheral device control and also a variety of tasks representative of ADL. The accuracy of gesture identification and the response time were assessed for both groups, and it was shown that although the performance of the FMG band was slightly decreased for the senior group, the intended gesture was still identified with good accuracy (76.5%). An average reaction time of 1.4 s showed that the senior group could easily understand the instructions and react accordingly.

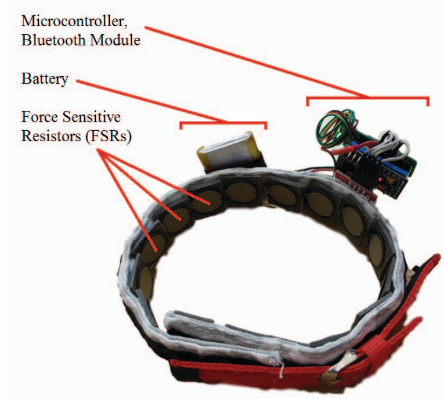
This paper is organized as follows: Section II describes the setup and experimental protocol used to collect data from participants. Algorithms used to process the collected data are explained in Section III. Obtained results are presented and discussed in Sections IV and V. The paper is concluded with suggestions for future work in Section VI.

II. Materials and Methods

A. Wrist Band for Collecting FMG Data

A custom FMG band was designed in-house for the purpose of this study. Force-sensing resistors, which demonstrate variable resistance depending on the amount of force applied to the active area, are used to collect force myography data. The designed band has 16 force-sensing resistors (FSRs) (FSR 400, Interlink Electronics, Inc., Los Angeles, CA) spaced 2 cm apart in a row. A microprocessor (ATMega328, Microchip Technology, Chandler, AZ) was used to collect and transmit data. FMG data was collected from each FSR at a sampling frequency of 10 Hz. Raw data values, ranging from 0 to 1023, were time stamped, transmitted to an on-site computer via Bluetooth connection, and saved for offline processing. Participants donned the FMG band on the wrist of their dominant hand, approximately 2.26 cm proximal to the radial and ulnar styloid process surface landmarks that identify the wrist (Fig. 1), and the FSR sensors were positioned to be in contact with the participants' skin. As such, the designed band is portable, wireless, and easily configurable for each participant.

(a)



(b)

Fig. 1: FSR wrist band used for data collection: (a) positioning of the band on a participant's wrist. The green light indicates that the module is on; (b) closer view of the band.

TABLE I: Summary of participants' information.

	Total Number	Gender M:F	Average Age	Number of Right Handed
Non-senior	5	3:2	25.4	5
Senior	5	4:1	67	5

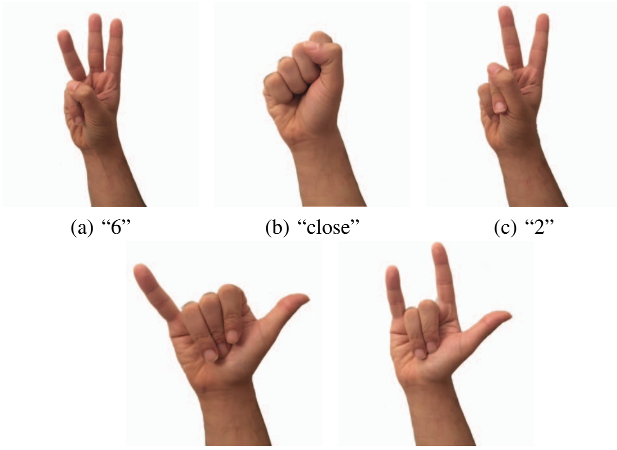
B. Participants

Participants were recruited from the students, faculty, and staff of Simon Fraser University. Inclusion criteria required participants to be able to follow instructions of the experimental protocol and perform the demonstrated gestures/tasks to completion. Volunteers with self-identified neurological or musculoskeletal barriers to functional movements of the upper extremities were excluded from participation. The Office of Research Ethics at Simon Fraser University approved the study protocol and all participants provided informed and written consent. A total of 10 volunteers participated in this study. Participants aged less than 60 years were assigned to the "non-senior" group and participants with at least 60 years of age were assigned to the "senior" group. Table I summarizes participants' information.

C. Study Protocol

Participants were asked to perform three repetitions of a test sequence consisted of three phases, namely: training, online testing, and household tasks. The FMG band was removed after each repetition and was donned again after a rest period. A brief description of test phases follows:

- During the **training** phase, participants were instructed to perform a set of predefined hand gestures, namely "6", "close", "2", "Y", and "I love you", based on the American Sign Language (Fig. 2). These gestures were used to control the user interface and were experimentally selected based on their distinguishability from the gestures most commonly used in object grasping and



(a) “6” (b) “close” (c) “2”

(d) “Y” (e) “I Love You”

Fig. 2: The control gestures used in the study protocol.

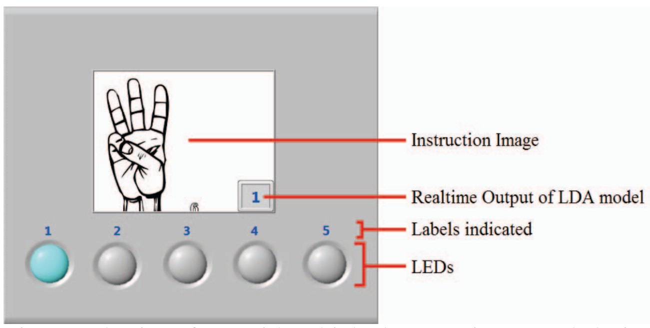


Fig. 3: The interface with which the user interacted during the online testing phase.

manipulation. Each gesture was repeated four times and in each repetition, the gesture was held for 5 s.

- During the **online testing** phase, participants received visual instructions to perform and hold each of the control gestures (Fig. 2) in a continuous succession. Each gesture was demonstrated four times during the online testing phase in a random sequence and was displayed for 10 s.
- During the **household tasks** phase, participants performed a series of tasks representative of ADL. These tasks were based on upper extremity diagnostic measures such as the Rating of Everyday Arm-use in the Community and Home (REACH) [34]. This phase was included to evaluate how the proposed platform would perform in an unconstrained setting. Household tasks were performed in a self-selected manner and were as follows: buttoning and unbuttoning a shirt, wiping a table, picking up a cup, opening and closing a jar, and sorting a set of pens.

The FMG data collected during each of these phases were saved to be processed as follows in Section III.

III. Data Processing

During the training phase, raw FMG signals were recorded from participants while they performed the five predefined hand gestures. These signals were then normalized using the global minimum and maximum of the FMG data acquired prior to testing and, subsequently, served as a sample-by-sample input to train a multi-output Linear Discriminant Analysis (LDA) model developed using built-in machine learning functions in MATLAB R2016a. The LDA model was chosen due to its lower computational cost and comparable performance with more complex algorithms such as Support Vector Machine (SVM).

During online testing and household tasks phases, five classes were defined as the output of the trained multiclass LDA model. These classes corresponded to the predefined control gestures used for training the model (Fig. 2). Each input sample belonged to each class of the LDA model with a normalized score ranged from 0 to 1. This score for each class was calculated by dividing the likelihood of the sample belonging to that class by the sum of likelihood across the five classes. A threshold of 0.95 was used to decide the model output: If the score of an input sample being in a class was greater than 0.95, the model would output that class number. If no single class achieved a score greater than or equal to 0.95, the output for that sample would be announced as “undefined”.

A custom program was designed in LabVIEW 2014 to facilitate data collection in each phase of the study. Part of this program was a user interface (Fig. 3) which displayed the control gesture to be performed by the user. In the online testing phase, visual indicators (LEDs) on this interface showed when the control gesture was correctly identified by the trained LDA model.

IV. Results

A. *Outcome Measures*

In this study, three outcome measures were considered to evaluate the feasibility of using the proposed method as a smart-home controller.

- During the online testing phase, the accuracy was considered as the ratio of duration of correctly identifying a control gesture to the duration of displaying the visual instruction for that gesture. This outcome measure is an indication of the capability of the gesture identification model to correctly identify a sustained gesture. This measure also encompasses any role that the fatigue caused by holding the gesture might have on the variability of performance.
- During the online testing phase, the reaction time was defined to be the time between when the visual instruction was first displayed and the first instance when the control gesture was correctly identified. This measure indicates how complicated the displayed gesture was to perceive and perform.
- During the household tasks phase, inadvertent identification of specific control gestures was tracked. As described in Section II-C, in this phase, the participants performed samples of real-world activities while wearing the FMG band. Thus, this measure provides an indication of the likelihood of unintended triggering of paired devices controlled by the FMG band.

TABLE II: Summary of participants' reaction time to complete a gesture when prompted with an image.

	Control gesture reaction times (s)				
	"6"	"close"	"2"	"Y"	"I Love You"
Non-senior	1.1±0.56	0.7±0.2	0.8±0.4	0.8±0.83	0.9±0.25
Senior	1.8±2.66	1±2.57	1.3±2.61	1.6±2.03	1.9±1.74

TABLE III: Summary of maximum time during which an ADL task was misidentified as a control gesture.

	Continuous identification of control gestures (s)				
	"6"	"close"	"2"	"Y"	"I Love You"
Non-senior	0.3±1.76	1.3±0.98	1.4±0.98	0.8±0.54	1.6±0.95
Senior	0.9±0.96	3.6±6.49	0.9±2.07	1.2±0.96	1.3±0.63

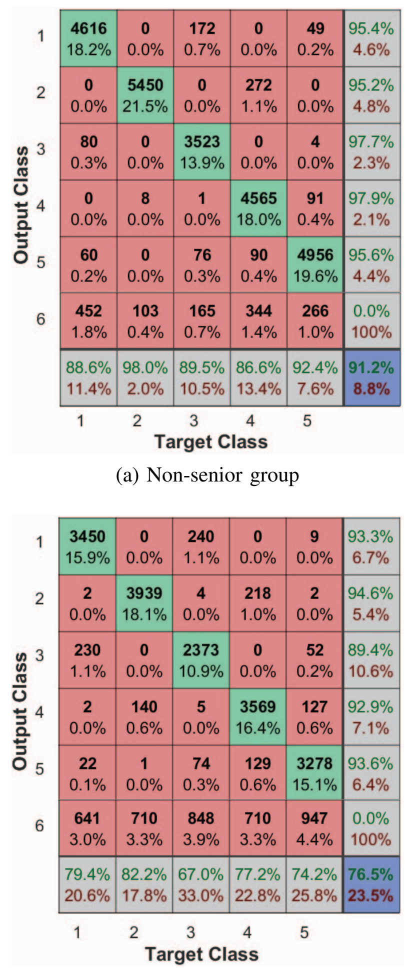
B. Experimental Results

The LDA classifier implemented on the data collected during the training phase achieved an accuracy of 97.57% for the non-senior group and an accuracy of 91.6% for the senior group.

During the online testing phase in which the participants were asked to mimic the control gesture displayed on screen and hold it for 10 s, non-senior participants demonstrated an average reaction time of 0.9 s. The held gesture was correctly identified in 90.66% ± 9.99% of the duration that the gesture was held after being identified correctly by the implemented identification algorithm. The senior group successfully performed the gesture within an average time of 1.4 s of displaying the visual instruction. In this case, the identification algorithm achieved an accuracy of 75.11% + 15.61% for the duration of time that a specific gesture was held. A breakdown of reaction times (Table II) showed that performing the control gesture "6" took the longest, while the participants had the fastest reaction to performing the control gesture "close".

One of the objectives of this paper was to investigate whether the proposed platform could distinguish between performing the household tasks during ADL and making one of the predefined control gestures. Therefore, the duration of time in which a control gesture was mistakenly identified during performing ADL tasks was evaluated. The result was that the average time of misidentification was 1.45 s over all gestures for the senior group and 1.25 s for the non-senior group. The breakdown of duration in which one of the ADL tasks was mistakenly identified as one of the gestures is provided in Table III.

The performance of the LDA algorithm is presented in form of modified confusion matrices in Fig. 4. The sixth row in these matrices corresponds to cases in which the 95% threshold for labeling a performed gesture as one of the control gestures was not reached (Section III). It is observed that lower accuracy achieved by the senior group is mostly due to inability to recognize the performed control gesture. For this group, the five predefined control gestures were mislabeled as "undefined" in 17.9% of the cases. These misidentified cases accounted for an error of 5% for the non-senior group.



(a) Non-senior group

(b) Senior group

Fig. 4: Confusion matrix for control gestures during the online testing. Classes 1-5 correspond to the following gestures: "6", "close", "2", "Y", and "I Love You". Class 6 of the output denotes "undefined", *i.e.*, unrecognized gestures. Red and green squares indicate the number/percentage of incorrect and correct classifications, respectively. The gray row and column show the gesture specific accuracy. The blue box shows the overall accuracy.

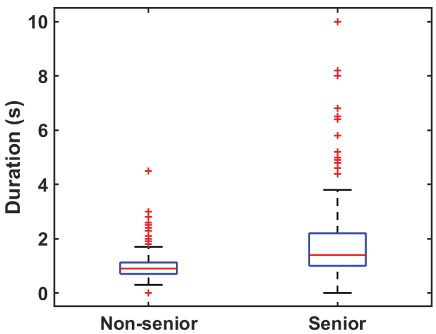


Fig. 5: Variations of reaction times over all gestures for senior and non-senior participants during online testing.

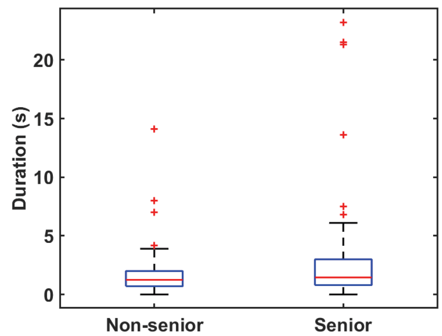


Fig. 6: Variations of time during which an ADL task was misidentified as a control gesture.

V. Discussion

In this study, we proposed an FMG-based platform to enhance current systems designed to improve the independence of seniors in performing ADL in their home environment. Since the preliminary acceptance of new technologies and the continued adherence to them depend on several key factors such as cost (monetary, time, effort, psychological), usability, obtrusiveness, and stigmatization [35], it is critical to take into account these considerations in order to design effective assistive technologies. Incorporating the FMG technology into the proposed wearable design addresses these concerns and reduces the likelihood of its being misplaced or lost like hand-held devices. Moreover, the implemented data processing and machine learning algorithms allows for an autonomous system that does not require deep user menus and cluttered designs which can be frustrating for those with failing memories, weak eyesight, and/or degrading motor skills [36].

The performance of the designed platform was assessed in a scenario in which an LDA-based classification algorithm was trained for each participant performing a set of predefined gestures. The online performance of this algorithm was then evaluated when the participant was performing either one of the control gestures or an unconstrained ADL task. It was observed that the senior group demonstrated longer reaction times compared to the non-senior group (Table II). However, considering that senior participants did not report any difficulties in understanding and following the given instructions, this result can be partially attributed to the general slowing of information processing and longer reaction time due to the aging process [37] and, therefore, might be improved with additional practice.

Figure 5 depicts the variations of reaction times of each group across all three repetitions of the experimental protocol and shows that senior participants also demonstrated a larger variability in reaction time. A detailed discussion on the reasons behind this observation is possible by an extensive study in which FMG data are collected while senior participants perform a comprehensive set of gestures and tasks [32], but this is beyond the scope of this paper.

Accuracy measures obtained in each of the test phases, *i.e.*, the training accuracy, the percentage of correctly identifying a gesture for the duration that it was held, and the percentage of incorrectly identifying an ADL task as a control gesture, showed that non-senior participants achieved a better accuracy. This result is not unexpected considering that senior participants have lower muscle tones and that they are more susceptible to fatigue, joint stiffness, and diminishing awareness of the effort they are exerting throughout the time that a gesture is held. These factors might affect the information content of FMG signals. However, this issue might be resolved with extending the training phase during which the LDA classifier is tuned to identify control gestures based on collected FMG data. The research on this topic is ongoing. Nevertheless, the current accuracy of the implemented algorithm can be considered acceptable at 76.5%.

The percentage of incorrectly announcing an ADL task as a control gesture is also an indication of the likelihood that a paired technology might be triggered unintentionally by our proposed control method during unconstrained movements of ADL. The variations of this measure for both groups across all of repetitions of the testing protocol are depicted in Fig.6. It can be observed that these variations fall approximately within the same range for both groups. This result is encouraging as it shows that the system demonstrates similar usability between senior and non-senior users according to this measure. Further research is required to choose optimal design choices to better distinguish ambient activity from control-specific movements.

This study was conducted as a first step to assess the usability of FMG-based technologies for senior populations. Therefore, it involved a smaller number of participants. The performance of the proposed platform can be enhanced by characterizing of inter- and intra-individual inconsistencies which requires recruiting a larger group of volunteers and implementing a more extensive training phase. Moreover, the algorithm should take into account the effects of age-associated changes on motor and cognitive abilities.

To improve the usability and acceptability of the proposed platform, future research should also explore developing unsupervised learning models of hand/arm activity which would discard the need to train the classification model and therefore, would eliminate the training phase in its current form. Such an improvement would result in minimal effort for recalibration on the user side, which is highly desirable.

VI. Conclusions

This paper presented a communication platform based on force myography techniques to be used primarily for providing assistance to the senior population. An array of 16 force-sensing resistors were integrated within a wrist band to monitor wrist movements while the user performed the study protocol. Ten participants were assigned to either non-senior or senior group according to their age and performed a number of predefined hand gestures. A supervised learning technique was implemented to identify the intended gesture as well as to distinguish between the control gestures and common activities of daily living. The proposed system achieved an accuracy of 76.5% for the senior group, showing the potential of using FMG-based technology to enhance current systems for assisting/monitoring the senior population within their home environment. Future research directions in this regard involve developing an unsupervised learning model of hand gestures, considering age-related effects in the obtained model, and combining the proposed interface with other sensing modalities to form a more comprehensive activity monitoring platform.

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