An Integrated Mobile Wireless System for Capturing Physiological Data Streams during a Cognitive-motor Task: Applications for Aging

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Abstract—**Cognitive, motor and perceptual processes diminish with age and thus limit adaptive capabilities of older individuals. Our hypothesis is that with aging there is decreased expression of these proactive adaptive capabilities. These experiments were designed to test this hypothesis by implementing an integrated approach to quantifying physiological characteristics in older individuals. We are working towards building an integrated wireless motion capture and physiological data monitoring system to quantify and data mine various physiologic and motoric streams in a controlled experimental environment. In this paper, synchronized motion capture and EMG data was obtained in young and old subjects performing a cognitive-motor task. We show that some, but not all baseline measures were significantly different in older compared to young subjects. Quantification of these baseline measures will allow us to develop new experimental paradigms that compensate for age-related decline in motor control, sensation, and cognition through brain-plasticity targeted training in rich learning environments.**

Index Terms—**motion capture, electromyography, analysis of variance, principal component analysis.**

I. INTRODUCTION

UNTIL recently, the dominant view was that aging was associated with irreversible cognitive and motor decline. Poor performance on cognitive and motor tasks and subsequent difficulty in performing goal-directed behavior are prevalent among the elderly [1]. This is thought to result from a decline in proactive processes in the brain [2] with eventual decline in cognitive and motor preparedness. For example, a ball thrown unexpectedly to an elderly person prompts a reaction of avoidance rather than the proactive preparedness leading to a safe catch. The leg muscle compensation expected when raising arms diminishes with age resulting in a loss of balance. Thus, with aging, there is an increase in the time it takes for the adaptive proactive processes to set in resulting in poor compensation [3].

The increased response latency observed in older adults can result from a perceptual, cognitive or motor deficit or a combination of deficits. Moreover, age-related changes in the musculoskeletal system and muscle physiology also contribute to motor slowing [4]-[6]. Given the dynamic

nature of this study, it is not possible to separate out the perceptual, cognitive or motor components of the task at hand. Rather, the primary objective of this initial study is to quantify the timing of movement dynamics and muscle activation patterns while performing a cognitive-motor task. The task we chose was a jump in which a visual cue signaled the subject to make the jump. Simultaneous motion capture and EMG data streams were obtained during the performance of this task. Our hypothesis is that with age, the time from muscle contraction to movement initiation decreases during the performance of a cognitive-motor task.

II. MATERIALS AND METHODS

A. Subject selection

Fifty-six healthy participants were recruited for this study. The age of the subjects ranged from 18-82 years. Data presented here was analyzed from 36 subjects due to technical difficulties during the recording sessions (missing markers, synchronization difficulties, poor EMG signal/noise ratio). The percentage of females in the study was 40%. None of the participants had overt neurologic, psychiatric or cognitive dysfunction (e.g., stroke, dementia, Parkinson's disease, etc). All measurements were recorded in the Motion Capture Lab at the University of Texas at Dallas. The study was approved by the Institutional Review Board at the University of Texas at Dallas. Subjects signed a consent form before the start of each session.

B. Motion capture acquisition and analysis

Motions were captured in the Motion Capture Lab equipped with 16 cameras (Vicon Systems). Data from all cameras were acquired at 90-120 frames per second. The details of this procedure are discussed in [7].

C. EMG acquisition and analysis

EMG Ag-Cl electrodes were used to record muscle activity of limbs. From these signals, we extracted the time of onset, peak latency, amplitude and other parameters from 12 muscles (6 on either side). On the upper extremities, four electrodes were placed on biceps, triceps, and forearm flexor and extensor muscles. On the lower extremity, two electrodes were placed on the tibialis anterior and the gastrocnemius muscles respectively. The EMG signal was

amplified and band-pass filtered (20-450 Hz) by the wireless system (Delsys, Boston). The sampling rate was set to 1000 Hz.

D. Integrating motion capture and EMG data streams

Motion capture and EMG data streams were synchronized. MATLAB (Mathworks) served as the main controller that sent a trigger to EMG and motion capture systems to start simultaneous acquisitions via a 'trigger module' and communicated with MATLAB via the Data Acquisition Toolbox (Mathworks). The processed EMG signal was full-wave rectified and down-sampled to 120 Hz to make it uniform with the motion capture system which captures data at 120 samples per second.

E. Experimental design

Subjects were divided into 3 groups: Old (61-90), Young-Old (31-60) and Young (15-30). Subjects performed a cognitive-motor task in which they had to jump on a sensor mat as quickly as possible in response to a cue. The image of the mat was displayed on a projector screen. Data acquisition during each trial began when the subject stepped on a sensor mat. When the subject steps on the mat, the cue "Ready?" is displayed on the screen. After an interval of 5 seconds, the word "Jump" appears on the screen. The subject is told to jump on the mat as soon as he/she sees the word "Jump". If the subject jumps before the appearance of "Jump", the word "False start" is displayed and the trial is repeated. Motion capture and EMG data was obtained during each of the 15 trials.

F. Data analysis

We performed a One-way Analysis of Variance (ANOVA) on each of the parameters across the 3 age groups followed by a post-hoc Tukey test. A p-value of < 0.05 was used as the criterion for statistical significance. Next, we performed a PCA analysis on the dataset to evaluate the relationship between variables. Since the units of these variables were different, we standardized the data by dividing each column by its standard deviation. Next, we were interested in determining whether the entire set of means distinguishes the three age groups. To achieve this, we derived a new set of variables called *canonical* variables that are linear combinations of the original variables such that group differences are maximized. To achieve maximum discrimination, we needed maximum separation between the groups and minimum separation within the groups. Using multivariate analysis of variance (MANOVA), we decompose the ratio of within-groups sum of squares and cross-products matrix (H) to the between-groups sum of squares and cross-products matrix (E).

III. RESULTS
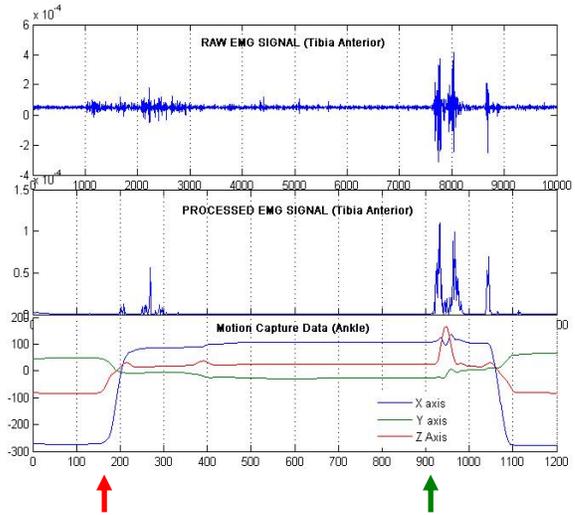
Data reported here was collected from 36 subjects.

Fig. 1. EMG and motion capture data during the jump

EMG and motion capture data from one trial is shown in Figure 1. The EMG data (top panel) is from the right tibialis anterior muscle and motion capture data is from the toe segment. The trial starts when the subject steps on the mat (red arrow) followed by the jump (green arrow). The jump activity is recognized by a notch in left ankle position along Z-Axis. The onset of EMG signal (contraction of tibialis anterior in this example) occurs prior to the jump (as the subject prepares to jump). Comparatively, not much muscle activity is seen simply stepping on the mat. This pattern varied with each trial and each subject, as EMG activity is stochastic in nature. Data was analyzed for the jump movement.
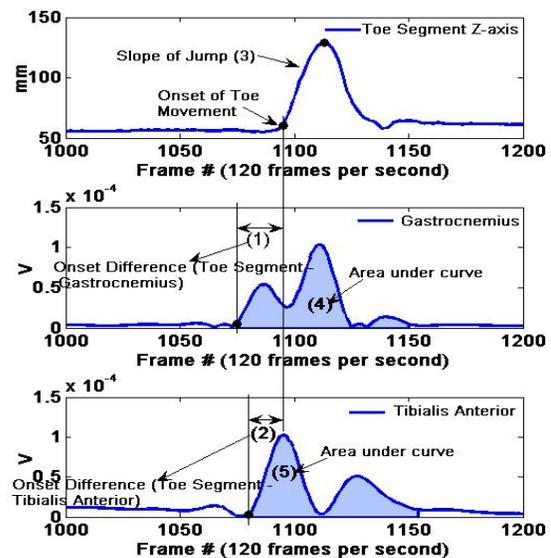

Fig. 2. Parameters extracted from the jump

Figure 2 shows a list of parameters quantified for the

experiment which was measured from the synchronous time series of motion capture and EMG.

A. ANOVA analysis

One way analysis of variance was performed across the 3 age groups for the parameters. The time difference between onset of gastrocnemius contraction to the initiation of the toe segment movement was significantly different for the old (p< 0.05) and young-old (p<0.01) groups (Fig. 3A). The (*) denotes significance and error bars represent standard error of the mean (SEM) for each group.

Fig 3: ANOVA analysis on onset time differences between toe segment and two leg muscles. The old age group showed a 17% reduction in the onset of EMG contraction compared to the young group (272 ± 12 vs. 225 ± 17) which may suggest a decrease in preparation time before the onset of movement. When time onset for the tibialis muscle was used, the old group was not significantly different from the young and young-old group (Fig. 3B: young, p=.1; young-old, p=.4).
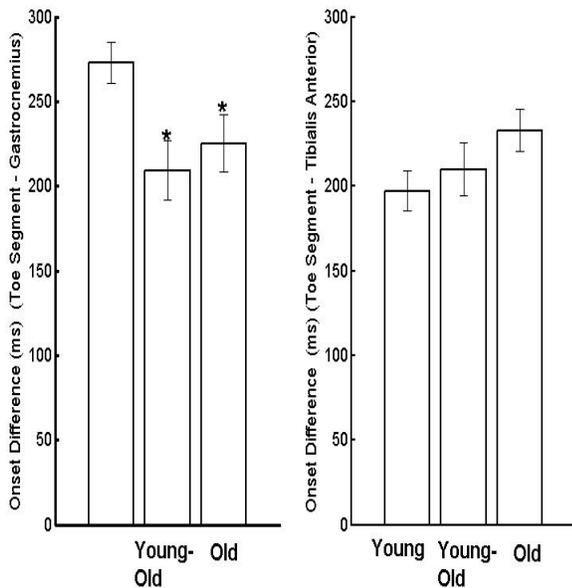

Figure 3 EMG to motion capture onset differences for A. Gastrocnemius and B. Tibialis Anterior muscle

B. PCA analysis

To evaluate the relationship between variables and their relevance to the participants' age-group, we did a PCA analysis on the dataset for all trials of 36 participants and corresponding 5 parameters. The factor scores for each trial of all participants grouped by age were projected on the first four dimensions (Figures 4 and 5). Together, these four dimensions (first four principal components) accounts for about 96.2% of the explained variance. In order to facilitate the interpretation, we represented the variable loadings on each principal component in the form of a vector. The direction and length of the vector indicated how each variable contributed to the two principal components.

The first component (Figure 4) explained 37.6% of the variance and was correlated with area under curve for both muscles gastrocnemius and tibialis anterior.

The middle age-group i.e. 31-60 has less contraction in both muscles. Most of the young age-group and old age-group has low and high activity in both muscles respectively, but both groups were prone to exceptions. The second component explained 22.8% of the variance and did not correlate with any variables. Due to this, separation between groups in first two-component space was not clear, as most groups were intermingled with each other. The third component (Figure 5) explained 19.3% of the variance and
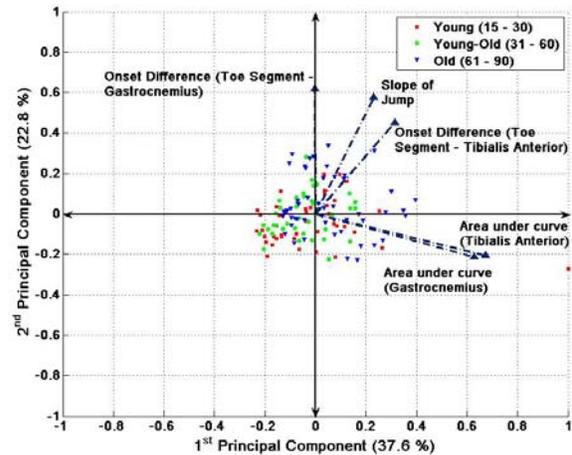

Figure 4. Loading plot diagram with five variables contributing to the dimensions 1 & 2 and score plot of 36 participants derived from principal component analysis
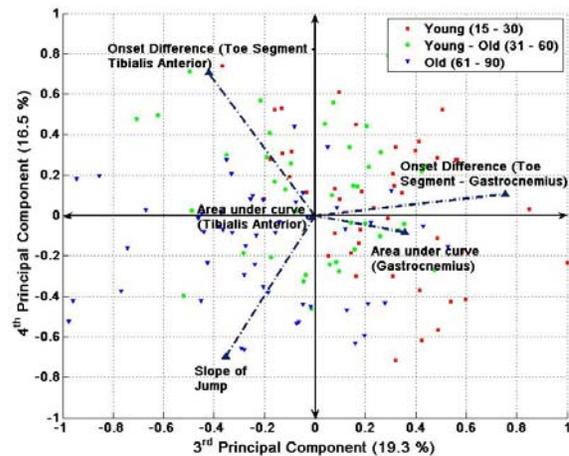

Figure 5. Loading plot diagram with five variables contributing to the dimensions 3 & 4 and score plot of 36 participants derived from principal component analysis.

was highly correlated with onset difference between toe segment and gastrocnemius, and it opposes the young group with highest onset difference to the old group that has low onset difference. The fourth dimension explained 16.5% of the total variance and was positively correlated with onset difference between toe segment and tibialis anterior, and

negatively correlated with the slope of the jump. It seems to isolate, to certain extent, the young and old groups.

After projecting the original dataset vector on the eigenvectors of HE^{-1} we obtained canonical variables that represented the maximum separation between groups. Figure 6 shows the a grouped scatter plot of the first two canonical variables that has more separation between groups than a grouped scatter plot of any pair of original variables. It shows three clusters of points representing each age-group, overlapping but with distinct centers. For this multivariate analysis of variance, we measure Wilk's lambda (Λ) as a test statistic by taking ratio of the determinants,

$$\Lambda = \frac{|E|}{|H + E|} \qquad (1)$$

For our data-set, we get $\Lambda = 0.47$. Using Wilk's Lambda (Λ), we also measured the F value by means of a set of equations mentioned in Appendix. The corresponding F value was 11.53, which suggests that the set of means of all groups were significantly different from each other. Using the simple dendrogram plot (not shown) of the three group means in Figure 6, we can show that, with respect to extracted variables the young and young-old age groups are closer to each other than old age-group.
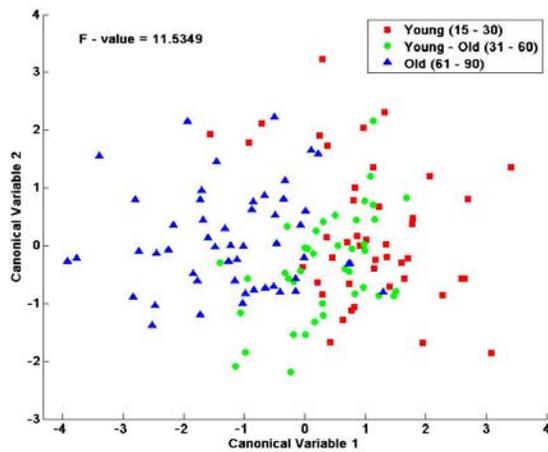

Fig. 6. A grouped scatter plot of the first two canonical variables showing more separation between three age groups.

DISCUSSION AND CONCLUSIONS

This study supports earlier studies that showed that the EMG signal occurs before the onset of movement [8]. Some studies have also documented the effects of age on anticipatory EMG activity during a variety of motor tasks and postural adjustments [9]. Our study shows that multidimensional techniques used on synchronized motion capture and EMG data reveals the performance differences between the three age groups using the extracted parameters. While this experiment provides data for a single joint segment and muscle, it is likely that more information will be generated by integrating data from multiple joints and muscles. In future studies, we plan to implement more complex cognitive-motor experiments (involving more sensors like goniometry, accelerometry, galvanic skin response and EKG) to identify the declining physiological characteristics in the aging.

This study is an initial step in a direction to develop an integrated environment for the simultaneous measurement of motion and physiology expressed in the dynamics of human action. This will facilitate the development of a mathematical model that integrates these parameters to extract feature vectors characterizing both reactive and proactive physiological processes. The accumulated data will serve as a basis for pursuing the long-term goal of developing interactive wireless devices to support a variety of cognitive and physical training activities for maintaining and improving cognitive and motor function in the elderly.

APPENDIX

An estimate an F can be calculated through the following equations,

$$F_{approx}(df_1, df_2) = \left(\frac{1-y}{y}\right)\left(\frac{df_2}{df_1}\right)$$

$$df_1 = p(df_{effect}); p = \textit{No. of variables}; df_{effect} = \textit{No. of groups - 1}$$

$$df_2 = s\left[(df_{error}) - \frac{p - df_{effect} + 1}{2}\right] - \left[\frac{p(df_{effect}) - 2}{2}\right]$$

$$y = \Lambda^{1/s} \quad ; \quad s = \sqrt{\frac{p^2(df_{effect})^2 - 4}{p^2 + (df_{effect})^2 - 5}}$$

REFERENCES

[1] J. E. Fisk., and C. A. Sharp, "Age-related impairment in executive functioning: Updating, inhibition, shifting, and access," *Journal of Clinical and Experimental Neuropsychology*, *26*, pp. 874–890, 2004.

[2] D. J. Tisserand, and J. Jolles, "On the involvement of prefrontal networks in cognitive ageing," *Cortex*, *39*, 1107–1128, 2003.

[3] J. Cerella, "Aging and information-processing rate," In Birren, J.E., & Schaie, K.W. (eds.), *Handbook of the psychology of aging* pp. 201–221, San Diego: Academic, 1990.

[4] H. Kinoshita, and P. R. Francis, "A comparison of pretension force control in young and elderly individuals," *European Journal of Applied Physiology and Occupational Physiology* 74 (5), pp.450–460

[5] A. E. Graves, K. W. Kornatz, R. M. Enoka, "Older adults use aunique strategy to lift inertial loads with the elbow flexor muscles," *Journal of Neurophysiology* 83 (4), pp. 2030–2039, 2000.

[6] C. S. Klein, G. D. Marsh, R. J. Petrella, and C. L. Rice, "Muscle fiber number in the biceps brachii muscle of young and old men," *Muscle & Nerve* 28 (1), pp. 62–68, 2003.

[7] G. N. Pradhan, N.D. Engineer, M. Nadin, and B. Prabhakaran, "Integration of motion capture and EMG data for Classifying the Human Motions," *Intl, Workshop on Ambient Intelligence, Media, and Sensing (AIMS)* , April 20, 2007, Istanbul, Turkey

[8] F. Lacquaniti, and C. Maioli, "The role of preparation in tuning anticipatory and reflex responses during catching," *J Neurosci.*, 9(1), pp. 134-48, Jan 1989.

[9] I. Melzer, N. Benjuya, and J. Kaplanski, "Age-related changes of postural control: effect of cognitive tasks," *Gerontology*, 47(4), 189-94, Jul-Aug, 2001.