# Analyzing Motoric and Physiological Data in Describing Upper Extremity Movement in the Aged


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## ABSTRACT

Cognitive functions, motoric expression, and changes in physiology are often studied separately, with little attention to the relationships, or correlations, among these entities. In this study, we implement an integrated approach by combining motion capture (action) and EMG (physiological) parameters as synchronized data streams resulting from the action and associated physiological data. Our experiments were designed to measure the preparatory movement capabilities of the upper extremities. In particular, measurement of changes in preparatory activity during the aging process are of interest to us, as the attempt is to develop means to compensate for loss of adaptive capabilities that aging entails. To achieve this goal, it is necessary to quantify preparation phases (timing and intensity). We measured motion capture and EMG parameters when subjects raised their arms without constraint (condition one) and raised their arms while holding a ball (second condition). Furthermore, on comparing aging and young participants, we confirmed that with aging the temporal relationships between actual movement and the preceding EMG signal change.


## Categories and Subject Descriptors

J.3 [**Life and Medical Sciences**]: [Health, Medical Information systems]

## General Terms

Integration analysis


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## Keywords

Electromyogram, motion capture, feature extraction, multivariate analysis of variance, factor analysis


## 1. 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. As the upper extremity movements are pervasive in our everyday lives, the impact of aging on them is of special relevance. This pertains to successful actions involving arm movements, as well as to the possibility of accidents (abrupt change of position can result in falls). Thus, it becomes very important to capture and analyze the quantitative description of the motoric behavior of the upper extremity movements across various age groups.

However, evaluating the aging effect in upper extremity movements has some strong challenges in form of variety, complexity, and the range of motions [13]. Some researchers [14, 2, 7, 9] have studied upper extremity movements, but they have evaluated the movements on a "coarse-grained" basis. For capturing how aging affects movement, it is necessary to get down into "fine-grained"' analysis and become sensitive to specific and minor changes in motoric expression. The reason being, through brain plasticity, we want to compensate for the loss, and this has to be specific.

In this paper, we aim to quantitatively analyze the characteristics of simple, upper extremity movement of raising the arms with two different conditions across young and old participants. To carry detailed and systematic analysis, we incorporated the two sophisticated techniques such as:

- 3D motion capture that aid in mapping the complex human motion in the three dimensional (3D) space. Here, a participant wears special markers that can be tracked by cameras in the 3D space.
- Electro-myograms that track the contractions of different muscles causing the body joints to move. A surface

EMG sensor monitors muscle contraction during body movements.

The integrated analyses of the body motions based on 3D motion capture data and EMG helps in understanding the correlation between different muscle actions and the corresponding body joint movements across various age groups. Also, such kind of database and the associated analyses stimulate several applications including: (a) designing rehabilitation programs for patients with restricted movements (due to accidents or illness, stroke, arthritis) and other neurological populations including dementia, Parkinson's disease, etc. (b) developing adaptive neuro-prosthetic devices that improve co-ordination and provide smoother and easier movements.
However, integrated evaluation and analyses of 3D motion capture data and the associated EMG's pose several challenges as well. First is the variation in speed and trajectory of the motions. Even though attempts can be made to control the duration of a task, motion speed can vary from participant to participant, as well as for the same participant. These variations can cause wide fluctuations in the 3D motion capture data. Electro-myograms can also show wide variations due to the differences in human physiological characteristics.

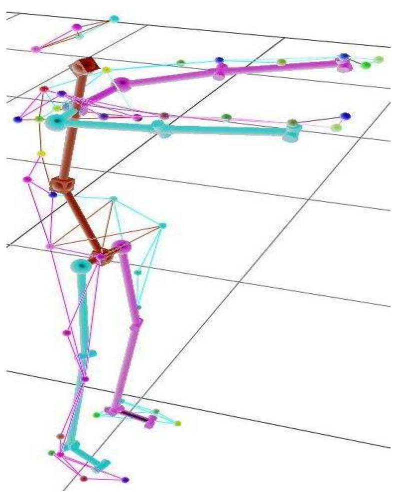

**Figure 1: The final posture of normal raise arm activity.**

## 2. RELATED WORK

When young individuals raise their arms, their leg muscles contract to compensate for the change in center of gravity to prevent loss of balance. In aging, this compensation expected when a person raises his/her arms diminishes and the individual loses his/her balance by raising the arms. Research shows that the electromyography (EMG) signal occurs before the action [1, 5]. Studies have also documented the effects of age on anticipatory EMG activity during a variety of motor tasks and postural adjustments [8] and general decline of adaptive capabilities [10]. One study examined anticipatory tripping behavior in young and old subjects and found that slightly increased muscle activity was observed in tibialis anterior and soleus muscles in older subjects [11].

In addition to simple movements, older subjects make use of additional (compensatory) limb movements to maintain balance during actions such as walking, catching a ball or raising arms and reflect a decline in maintenance of posture and stability. In [12], authors revealed the performance differences between the three different age categories by applying univariate analysis of variance and principal component analysis on the extracted parameters from a single joint segment and muscle using synchronized motion capture and EMG data. 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. Over the years, many behavioral parameters have been used to study decline in sensory-motor and cognitive performance. The most commonly used measures include reaction time [3, 6, 15], movement time and velocity of movement [4]. Many of these studies focus almost exclusively on the kinematics and biophysical aspects of motion. However, preparation of movement is an important component that has been addressed in only a few aging studies. Our study addresses this proactive component in aging in the form of synchronized motion capture and EMG data streams during the action of raising the arms.

## 3. MATERIAL AND METHODS

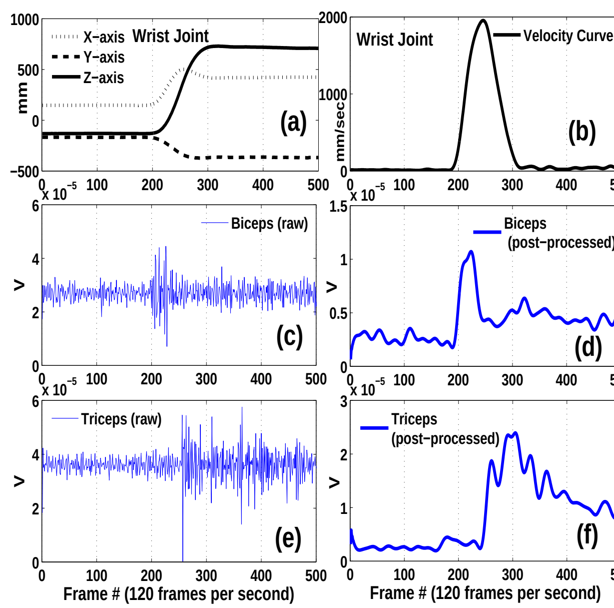


**Figure 2: (a), (c), (e): Raise arm activity with corresponding motion capture data for right wrist joint and synchronous EMG activity in muscles biceps and triceps, (b): Velocity curve for the wrist joint, (d), (f): Post-processed EMG signals from biceps and triceps respectively.**

### 3.1 Subject selection

30 healthy participants were recruited for this study. The age of the subjects ranged from 20-80 years. Data presented here was analyzed from 20 subjects due to technical difficulties during the recording sessions (missing markers,

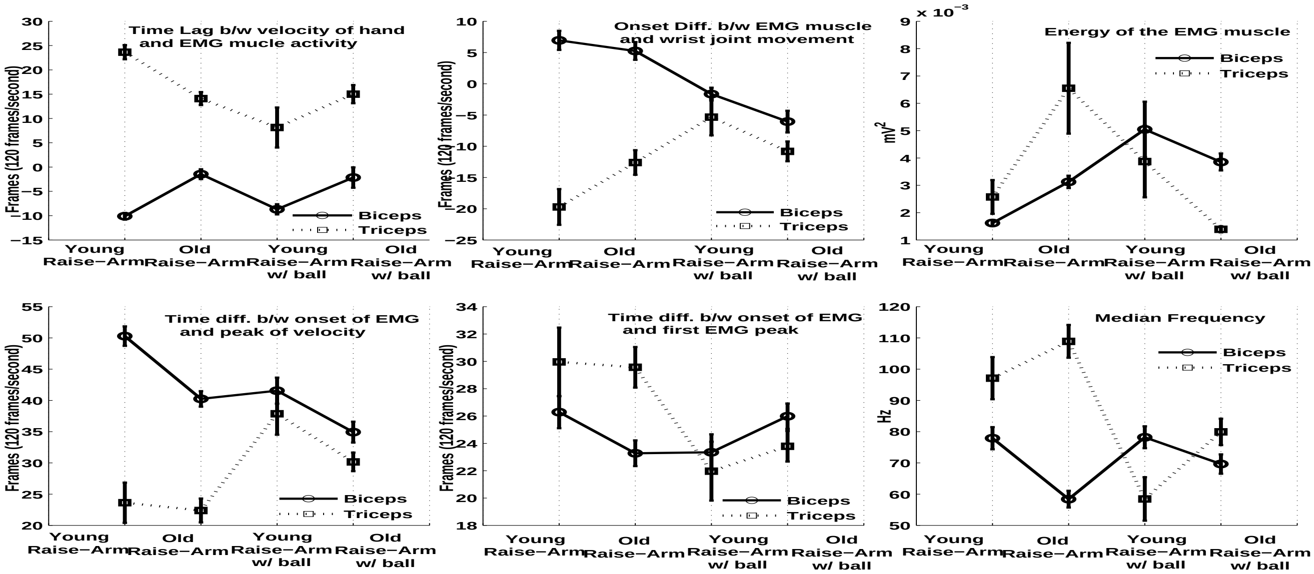


**Figure 3: The error-bars for extracted features of biceps and triceps across young and old for both experiments.**

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.

## 3.2 Motion capture acquisition and analysis

Motions were captured in the Motion Capture Lab equipped with 16 cameras (Vicon Systems). A participant wore a suit of non-reflective material and about 44 markers were attached over the body covering each joint. Placement of markers corresponded to the area of interest. The data from the motion capture cameras were acquired in the form of frames at a speed of 120 frames per second. A data station (i.e., the PC with the motion capture software) combines the data from all cameras into one matrix (per participant). Each row in the matrix corresponds to 1 frame of data. For a single human motion of, let us say 10 seconds, the matrix consist of 1200 rows. Since human body has 19 major segments (head, shoulder, hand, etc) and each segment has translation (3 columns one for each dimension X, Y, and Z) and rotation (3 columns for X, Y, and Z), we have a total of 114 columns in the motion capture data matrix.

## 3.3 EMG acquisition and post-processing

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) with a sampling rate set to 1000 Hz. Further, the signal was full-wave rectified and filtered using $4^{th}$ order, 10Hz low-pass cutoff Butterworth filter.

## 3.4 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 downsampled to 120 Hz to make it uniform with the motion capture system which captures data at 120 samples per second. Figure 2 (a), (c), and (e) shows the synchronous 3D motion capture data for the right wrist joint and corresponding EMG activity in muscles biceps and triceps for normal, raise arm activity. Figure 2 (d), (f) are the post-processed biceps and triceps muscular activity respectively (as discussed in Section 3.3). Figure 2 (b) is the velocity curve for the right wrist joint.

## 3.5 Experimental design

Subjects were divided into 2 groups: Old (51-80), and Young (20-50). Subjects performed upper extremity movement, in which they have to raise the both arms up to shoulders (approximately 90°) as shown in Figure 1 in response to a visual cue displayed on the screen. For every trial, we have a initial baseline activity by displaying cue "Ready?" on the screen where subject becomes idle and pays attention to the screen, and then after a span of 2-3 seconds follows the visual cue "Raise!" where he/she starts activity of raising the arms. We designed preparatory time frame, to have control on subject's activity and to make sure he/she doesn't perform unnecessary movements that may give false positives. For each subject we captured the raise arm activity with two conditions. (1) Normal, free raise arm movement; (2) Raise arms by holding an object (in our case, football (soc-

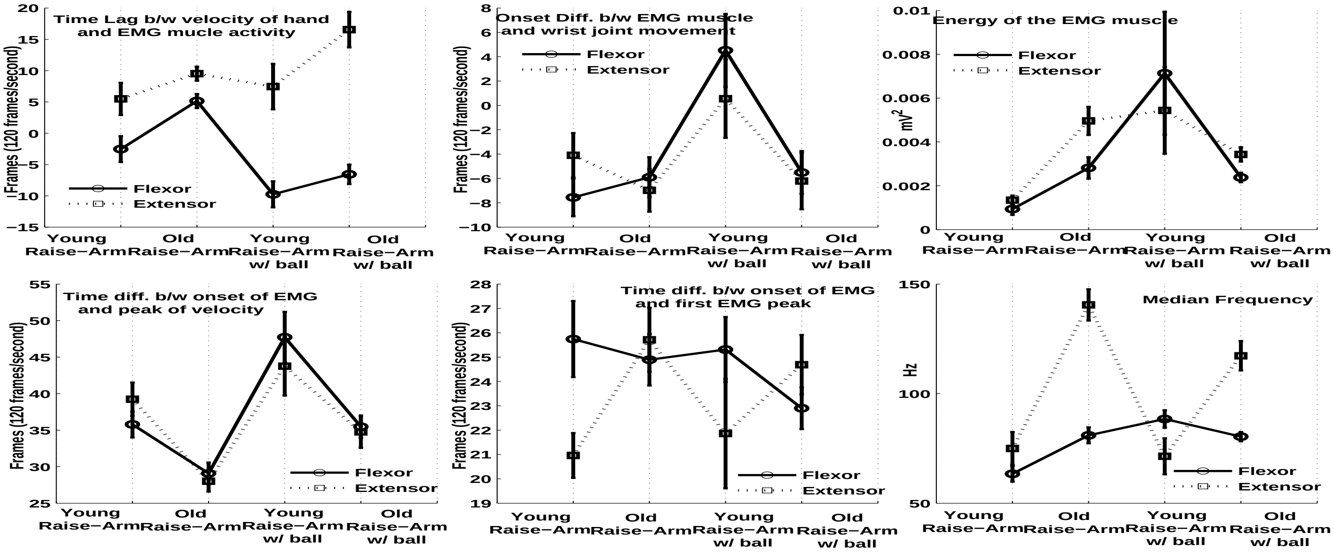


**Figure 4: The error-bars for extracted features of flexor and extensor across young and old for both experiments.**

cer) [Weight 410-450 gms])) with both hands. We chosen soccer ball because of its familiarity and dimensions (circumference = 27-28 inches), which makes it comfortable to raise. Moreover, its weight is ideal not only to handle by any subject regardless of age, but also sufficient to put an extra force on muscular activity as compared to just raise arms. We collected 10 trials each for both conditions from every subject. So, as we are analyzing data from 20 subjects (9 young + 11 old), we have total of 400 trials or motions performed during our experiments.

### 3.6 Feature Selection and Extraction

For raise arm activity, we mainly focus on active, upper extremity muscles such as biceps, triceps, flexor, extensor along with the 3D-movement of the wrist joint. To quantify the proactive components in the aging it is necessary to identify the temporal inter-relationships between the synchronous muscular and physical joint activities during the preparatory phase of raising activity. Thus, we extracted following quantitative features from each EMG muscle activity with respect to the wrist joint for each trial of raising the arms as follows:

1. Time lag between relative velocity of wrist movement and EMG muscular activity.
2. Onset difference between EMG muscle and wrist joint movement.
3. Energy of the EMG muscular activity.
4. Time difference between an onset of EMG muscle and the time at peak velocity of wrist joint
5. Time difference between an onset of EMG muscle and the time at first peak of EMG muscular activity.
6. Median Frequency of the muscular activity.

As the raising of arm activity is a functional movement, we cannot control the local speed of the arms across different subjects. The above first five parameters can be easily interpreted from the illustrated Figure 2 (b) and (d) for biceps and velocity of wrist joint (i.e. hand). The last parameter is the frequency-domain related parameter, which we can measure by applying Fast Fourier Transform (FFT) to the time series of EMG activity. Along with temporal parameters, it is important to study the effect of aging on both raise arm conditions using frequency characteristic of the muscular activity.

Figure 3 and 4 shows the error bars for the extracted features from the EMG muscles biceps-triceps and flexor-extensor respectively. The error bar for the each feature of the EMG muscle indicate the mean and standard deviation for the young and old participants across both raise arm conditions, normal raise arm and raise arm with ball. As we have 9 young participants, in each group of *"young raise arm"* and *"young raise arm with ball"* we have 90 measurements for the corresponding feature for each EMG muscle. Similarly, for 11 old participants we have 110 measurements in each group of *"old raise arm"* and *"old raise arm with ball"*.

## 4. DATA ANALYSIS

The acquisition of the raise-arm experiment with two conditions on two subject categories (i.e. young and old) lead us to four different kind of groups such as (1) Young doing normal raise arm, (2) Old doing normal raise arm, (3) Young doing raise arm with ball, (4) Old doing raise arm with ball. Moreover, as seen from Section 3.6, for every trial of any participant in any group, we have set of extracted features that gives temporal relationships between different muscles and movement of the joints.

To identify the differences between these different groups for analyzing the aging effect in upper extremity movements, we need to perform analysis of variance on the extracted features across these four groups. And, as we have multiple features for each trial, we form a multidimensional measurement space in which each trial is represented as a feature vector. Hence, we apply multivariate analysis of variance, where extracted features become the dependent variables and the groups become independent variables. The multivariate analysis of variance derives two terms in form of matrices as follows:

- sums of squares and cross-products of deviation for each trial's feature vector from their respective group mean, in short, within-groups sum of squares and cross-products matrix (E).
- sums of squares and cross-products of deviation for group mean from the grand mean, in short, between-groups sum of squares and cross-products matrix (H).

These two matrices can be used to calculate Wilks' lambda ($\Lambda$) as a test statistic in multivariate analysis of variance to investigate the differences between the means of groups on a combination of extracted features. $\Lambda$ is calculated as follows,

$$Wilks'\ lambda = \frac{|E|}{|H+E|} \tag{1}$$

Here, the determinant of the within-clusters sums of squares and cross products matrix $E$ is divided by the determinant of the total sum of squares and cross products matrix $T = H + E$. To investigate the data for multivariate differences, the null hypothesis that indicates no differences in the vector of mean features across groups is tested. If $H$ is large relative to $E$, then $|H + E|$ will be large relative to $|E|$ and there is maximum separation between the groups and minimum separation within the groups with respect to the entire set of quantitative features. Thus, we could reject the null hypothesis if $\Lambda$ is small (close to zero) because there is a significant difference between the set of means of features among the groups. Also, in multivariate analysis of variance, $\Lambda$ statistic can be transformed approximately to more familiar $F$-distribution which can represent the significance of difference between clusters by $F$-value and degree of freedoms (df). The higher values of $F$ indicates greater differences in the groups and rejection of null hypothesis.
Further, we derived a new set of variables called *canonical variables* that are linear combinations of the original dependent variables such that we can achieve maximum separation between the groups and minimum separation within the groups. On eigen-decomposing the matrix $HE^{-1}$ we get coefficients for the linear combinations of the original dependent variables in form of eigen vectors. On projecting the original features of trials on the eigenvectors of $HE^{-1}$ we obtain canonical variables that represent the maximum separation between groups. Thus, applying multivariate analysis of variance on the extracted, quantitative features we could evaluate the aging effect on the upper extremity movements through varying conditional experiments.

Now, our next stage is to compare and analyze the relationship between the extracted features for two different condition of raise arm (normal and with ball). We combine these two sets of features into a common structure called *"compromise space"* which is then analyzed using principal component analysis to reveal the common structure between the young and old participants. Hence, for each raise arm condition, we take the average measures of all extracted features for every participant across corresponding trials. That means, in both raise arm conditions, every participant is represented in form of average vector of extracted features. Thus, we form two *condition* matrices ($T_{normal}$ and $T_{ball}$) for raise arm experiment, where in each matrix, rows represent the participants and column represents the average value of extracted features (i.e. $T^{p\times f}_{normal}$ and $T^{p\times f}_{normal}$, where $p$ = number of participants (young + old) and $f$ = number of features). Both matrices are post-processed by centering and normalizing the column vectors as they may have heterogenous range of values, and analysis is carried further as follows:

1. Each matrix $T_{normal}$ and $T_{ball}$ defines inherently a structure for the performance of the young and old participants with respect to the corresponding raise arm condition, which can be derived by computing the scalar products between participants. The corresponding scalar product matrices are denoted as $S_{normal}$ and $S_{ball}$ respectively.

2. The weighted sum of both matrices gives compromise matrix as follows,

$$M_C = 0.5 \times S_{normal} + 0.5 \times S_{ball} \tag{2}$$

   As we have only two conditions to analyze, we distribute the weight uniformly among the scalar product matrices.

3. For analyzing the compromise matrix $M_C$, we use principal component analysis that explores the overall performance of the participant with respect both raise arm conditions. Since, compromise matrix is also a scalar product matrix, its PCA is given as,

$$M_C = Q \wedge Q^T \tag{3}$$

   The factor scores (i.e. the projection of the rows on the principal components of the analysis of $M_C$) are obtained as,

$$F = Q\wedge^{\frac{1}{2}} \tag{4}$$

   In this matrix $F$, each row corresponds to the participant and each column corresponds to the component. The compromise space is formed by first few principal components of the factor score matrix that carry total variance of $85-90\%$. And the factor scores for each participant that are mapped in compromise space represent the overall performance of the participant with respect to both raise arm conditions.

## 5. RESULTS AND DISCUSSIONS

In this paper, we are analyzing the aging effect on the upper extremity movements by comparing raise arm experiment performed by young (20-50) and old (51-80) participants in two different conditions (normal and with ball). In this section, we will present the results of two types of analysis,

- multivariate analysis of variance - that expresses the difference between two age groups across both conditions of raise arm activity.
- factor analysis - that analyzes the factors that are responsible for distinguishing the two age groups.

| Effect | $\Lambda$ | $F$ | p |
|---|---|---|---|
| Age $\times$ Condition | 0.11 | 9.64 | $< 0.01$ |
| Age (Young or old) | 0.44 | 2.76 | $< 0.01$ |
| Condition(normal or Ball) | 0.39 | 3.29 | $< 0.01$ |

**Table 1: Result for multivariate analysis of variance for differences between Age $\times$ Raise arm condition, Age, and Raise arm Condition.**

## 5.1 Multivariate analysis of variance

In Table 1, the first row indicates that there is a significant interaction between the aging effect and the two raise arm conditions with multivariate F-value = 9.64. This result is well supported, when 2-way MANOVA was conducted on the trials of all participants with both conditions. There was a significant multivariate main effect for age ($\Lambda = 0.44$, F = 2.76) when both raise arm conditions were merged under age effect. Also, there was significant difference existed within the raise arm conditions for all the extracted features ($\Lambda = 0.39$, F = 3.29). These results suggests that, the behavior of the EMG muscle associated with upper extremities have reaction on aging.
In order to interpret the results of the multivariate analysis

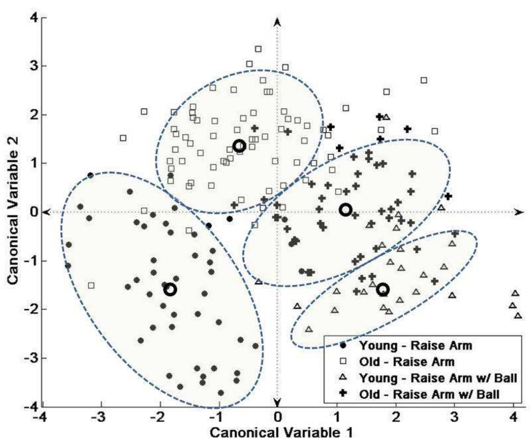


**Figure 5: The projection of individual parameter vector per trial for each participant across two experiments in canonical space.**

of variance on the extracted features across age and raise arm conditions, we derive canonical variables as discussed in Section 4, that represent each trial of the participant in low-dimensional canonical space. Figure 5 shows the two canonical variables for each trial across four groups with corresponding centroids. The virtual, approximate boundaries indicating four groups shows that there is maximum discrimination between the groups in defined canonical space. In Figure 5, the first canonical variable differentiates between the two raise-arm conditions (i.e. opposes the effect of the normal raise arm and raise arm with ball). While, second canonical variable differentiates according to age (i.e. opposes the effect of young and old). Thus, aging effect across both raise- arm conditions can be easily interpreted in the canonical space.

Also, to represent each individual participant in canonical

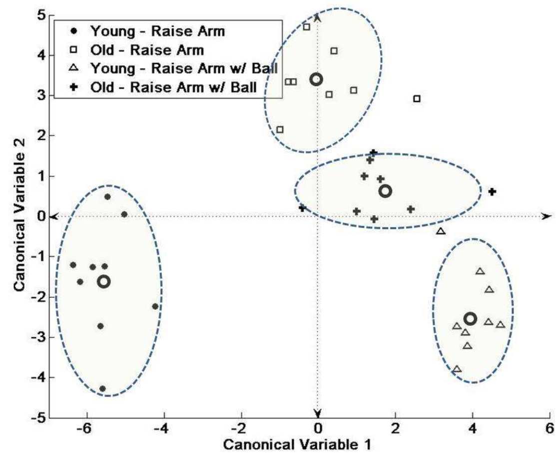


**Figure 6: The projection of mean parameter vector for each participant across two experiments in canonical space.**

space instead of each trial of every participant, we took the means of all trials for every participant for every raise arm condition and applied multi-variate analysis of variance with four groups and each entry in the groups was representing the vector of means of extracted features. Figure 6, shows the four groups, with two canonical variables representing each participant in four different groups. The canonical variable 2 clearly discriminates the old (positive side) and young (negative side) participants. The performance of the young participants varies more across canonical variable 1 in two raise arm conditions as compared to old participants.

## 5.2 Factor analysis

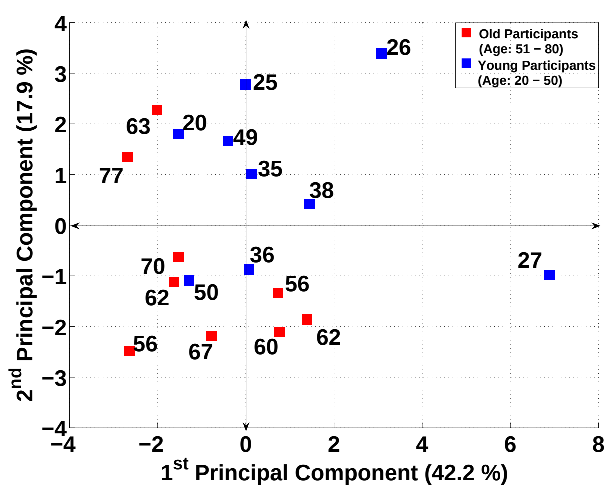


**Figure 7: The projection of each participant in the compromise space. (The numbers indicate 'age' of the participants.)**

The two condition matrices $T_{normal}$ and $T_{ball}$ contains the average measures of all extracted features for each young and old participants across respective trials. Figure 7 shows the *compromise space* in first two principal component axes that reveals the common structure between young and old participants. Each point (i.e. factor score from Equation 4) mapped in *compromise space* represents the combined performance of the corresponding participant across two raise arm conditions i.e. normal raise arm and raise arm with ball. As seen from Figure 7, second principal component (that explains 17.9% of total variance) opposes most of the young participants from the old participants. Due to real data sets, some participants may show different behavior as compared to other participants in the same group.

In addition, we also need to interpret the behavior of the

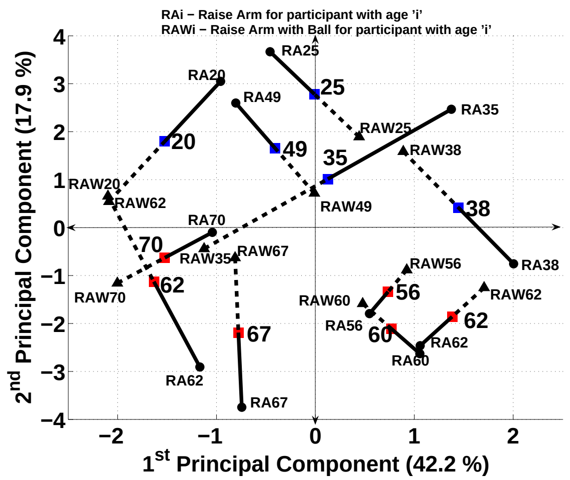


**Figure 8: The projection of some participants along with their projection of each performance in both experiment in the compromise space.**

every participant for each condition in the same space. This can be achieved by projecting the scalar product matrices $S_{normal}$ and $S_{ball}$ for each raise arm condition onto the compromise space. Figure 8 shows the projection of two raise arm conditions for six older and five younger participants in the compromise space. The projection of the participant is the centroid for the corresponding projections of two raise arm conditions. To make it simple for interpretation, in Figure 8, we have drawn line linking the position of each participant to it's corresponding positions for both raise arm conditions in the compromise space.

The original extracted features can be integrated into the compromise analysis by computing loadings using the standard approach similar to PCA. The loadings are the correlation between the original features and the factor scores. Figure 9 and Figure 10 shows the circle of correlation obtained for both raise arm conditions i.e. normal and with ball respectively. For the sake of representation, in Figure 9 and Figure 10, we show the correlation of the extracted features for individual muscles separately for the respective raise arm conditions. The features numbered from 1 to 6 are in same order as mentioned in Section 3.6. Generally, any correlation above 0.7 is considered significant, but as we work on real-life EMG data set that is prone to noise, we can lower the significance level to 0.4. Now in Figure 9, for biceps, we have energy of this muscle (3) negatively correlated with second principal component. That means, the participants having high biceps energy signals will lie towards the negative direction of principal component axis 2 in compromise space. As seen from Figure 7, mainly the old participants lie in this area. This result is consistent with the observation that old participants put in lot of force for the goal-directed, upper extremity movements as compared to younger ones. Similarly, we can observe the correlations of the different features for the both raise arm conditions to the principal component axes. Using these correlations and position of participants in the compromise space, we can interpret the effect of aging on the corresponding features of the EMG muscles.

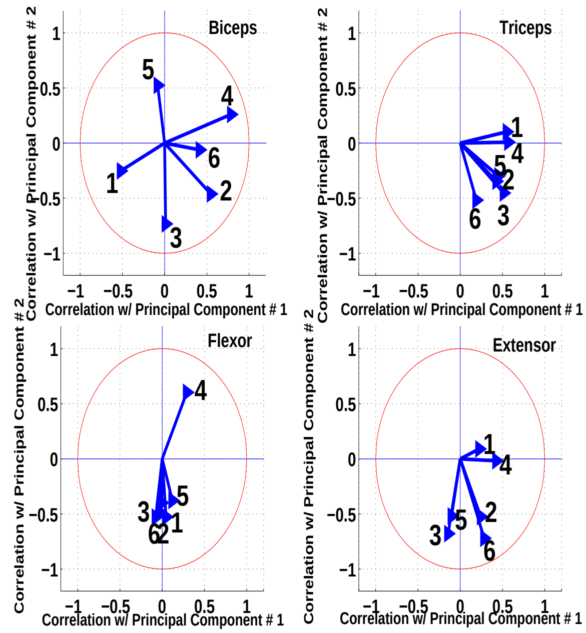


**Figure 9: The circles of correlation for normal, raise-arm experiment representing loadings for each hand sensor.**

## 6. CONCLUSION

In this paper, we evaluated the aging effect on upper extremity movements by conducting simple raise arm experiments across young and aged participants under two different conditions, (a) normal raise arm, and (b) raise arm with a football. We performed quantitative analysis on these conditions by extracting the timing and intensity related features from the synchronous data streams of motion capture and electromyogram sensors. This integrated analysis of upper extremity movements based on 3D motion capture data and EMG gave us the knowledge of interesting correlations between different muscle actions and the corresponding body joint movements related to upper extremity across young and old age groups.

We tested the differences in terms of extracted features across two age groups and also across two raise arm conditions using multivariate analysis of variance. The results shown that, there was a significant difference ($p < 0.01$) for all three kinds of effects such as age, condition for raise arm, and age $\times$ condition. We also performed canonical analysis, to show the maximum discrimination between different groups by achieving maximum separation between the groups and

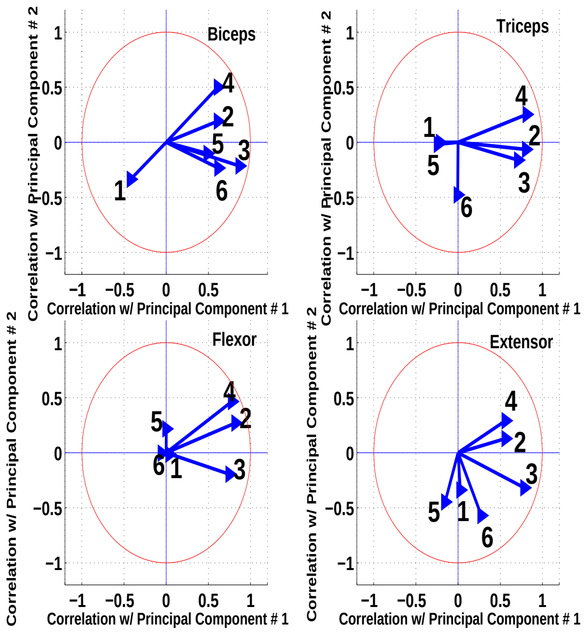


**Figure 10: The circles of correlation for raise-arm with ball experiment representing loadings for each hand sensor.**

minimum separation within the groups. Further, we analyzed the factors that were responsible for distinguishing between the groups using factor analysis. We measured the factor scores for each participant that were represented in the compromise space, which revealed the common structure between young and aged participants. Also, we integrated the original extracted features in compromise structure by computing the correlations between the factor scores and the features (i.e. loadings). Thus, using loadings, we interpreted the effect of aging on the features that were extracted using EMG muscles and body joints associated with upper extremity movements.
Along with aging applications, this gathered data, integrated analysis, knowledgable correlations have several applications including the design of rehabilitation and health care programs, developing adaptive neuro-prosthetic devices, and sports medicines.

## 7. REFERENCES


[1] D. Falla, A. Rainoldi, R. Merletti, and G. Jull. Spatio-temporal evaluation of neck muscle activation during postural perturbations in healthy subjects. *Journal of Electromyography and Kinesiology*, 14(4):463–474, 2004.

[2] E. Finch. *Physical rehabilitation outcome measures: a guide to enhanced clinical decision making.* Lippincott Williams and Wilkins, 2002.

[3] R. Gottsdanker. Age and simple reaction time. *Journal of Gerontology*, 37:342–348, 1982.

[4] R. Jagacinski, N. Greenberg, M. Liao, and J. Wang. Manual performance of a repeated pattern by older and younger adults with supplementary auditory cues. *Psychology and Aging*, 8:429–439, 1993.

[5] F. Lacquaniti and C. Maioli. The role of preparation in tuning anticipatory and reflex responses during catching. *Journal of Neuroscience*, 9(1):134–148, 1989.

[6] N. Lupinacci, R. Rikli, C. Jones, and D. Rose. Age and physical activity effects on reaction time and digit symbol substitution performance in cognitively active adults. *Research Quarterly for Exercise and Sport*, 64:144–150, 1993.

[7] P. McCrea, J. Eng, and A. Hodgson. Biomechanics of reaching: clinical implications for individuals with acquired brain injury. *Journal of Disability and Rehabilitation*, 24(10):534–541, 2002.

[8] I. Melzer, N. Benjuya, and J. Kaplanski. Age-related changes of postural control: effect of cognitive tasks. *Gerontology*, 47(4):189–194, 2001.

[9] M. A. Murphy, K. S. Sunnerhagen, B. Johnels, and C. Willén. Biomechanics of reaching: clinical implications for individuals with acquired brain injury. *Journal of NeuroEngineering and Rehabilitation*, 3(18):1–11, 2006.

[10] M. Nadin. *Mind - Anticipation and Chaos.* Belser Presse, 1991.

[11] M. Pijnappels, M. Bobbert, and J. van Dieën. Emg modulation in anticipation of a possible trip during walking in young and older adults. *Journal of Electromyography and Kinesiology*, 16(2):137–143, 2005.

[12] G. Pradhan, N. Engineer, and M. N. andBalakrishnan Prabhakaran. An integrated mobile wireless system for capturing physiological data streams during a cognitive-motor task: Applications for aging. In *IEEE Dallas Engineering in Medicine and Biology Workshop*, pages 67–70, November 2007.

[13] G. Rau, C. Disselhorst-Klug, and R. Schmidt. Movement biomechanics goes upwards: from the leg to the arm. *Journal of Biomechanics*, 33(10):1207–1216, 2000.

[14] D. Wade. *Measurement in neurological rehabilitation.* Oxford University Press, 1992.

[15] J. Yan, J. Thomas, and G. Stelmach. Aging and rapid aiming arm movement control. *Experimental Aging Research*, 24(2):155–168, 1998.