

Evaluating the Effect of Local Variations in Visually-Similar Motions on the Clustering of Body Sensor Features

Gaurav N. Pradhan
Department of Computer Science
Arizona State University
Tempe, AZ 85287
gaurav.pradhan@asu.edu

B. Prabhakaran
Department of Computer Science
University of Texas at Dallas
Richardson, TX 75083
praba@utdallas.edu

Abstract—Body Sensor Network-related applications such as assistive-living environment, orthopedic, physical medicines, and rehabilitation use wearable body sensors like motion trackers to track joint movements and electromyogram sensors to track muscular activities. These sensors provide information in the form of multidimensional time series data. Generally, for these applications, classification or similarity retrieval of human motions is performed by traditional clustering of dimensionally-reduced feature vectors based on joint movements and/or muscular activities. However, local variations in visually-similar sets of human motions cause them to group in different clusters resulting to a lower recall during retrieval. Hence, it is important to evaluate the effect of local variations on the given clustering of feature vectors.

In this paper, we represent the local variations in the form of quantitative attributes that are measured from sensors' time series data. And further, we propose a multivariate analysis of variance technique for evaluating the effect of quantitative attributes on the clustering results that are based on different configurations of feature vectors representing joint movements and muscular activities.

I. INTRODUCTION

Body sensor network (BSN) includes array of wearable sensors to recognize as well as to monitor movements and physiological conditions of individuals. In many BSN-related applications such as assistive living environment, motion rehabilitation, gait analysis and several orthopedic areas such as joint mechanics, prosthetic designs, and sports medicines, retrieving similar sets of human motions for the given motion query is of major importance. Over the last decade, much progress has been made in muscular signal analysis, processing, and pattern classification ([1], [5], [2]). In the area of human motion database, similarity-matching [7], indexing ([8], [14]) and content-based retrieval ([9], [11]) of human motions are being done. Recently, [4] performed the content-based retrieval of human motions based on the integrated effect of joint movements and muscular activities. Most of these methods used various dimensionality reduction techniques such as Piecewise Aggregation Approximation (PAA), Principal Component Analysis (PCA), Discrete Fourier Transform (DFT), Integral of Absolute Value (IAV) to extract low-

dimensional features from the multidimensional time series sensor data and perform classification or similarity retrieval based on traditional clustering of extracted features.

Our hypothesis is that the *local variations* within similar set of motions may get them distributed in different clusters inside the feature space causing the problem of false dismissals during similarity retrieval. In order to test this hypothesis, we need to evaluate the effect of local variations in visually-similar motions on the clustering of human motions based on the extracted features. In this paper, we define *local variations* in the form of quantitative attributes such as onset timing differences between joint movement dynamics and muscle activation patterns, strength of muscle contraction, velocity, acceleration, deceleration of joint movements etc.

Our objective is to find the relationship between the distribution of visually-similar motions in different clusters formed in feature space and the quantitative attributes that represent local variations in the corresponding visually-similar motions. In this paper, we propose a method that uses multivariate analysis of the variance, that identifies whether changes in quantitative attributes have significant effect on cluster membership for the respective visually-similar motions in the feature space. The detailed approach for multivariate analysis is discussed in Section III, where dependent variables are the quantitative attributes of visually-similar motions and independent variable is the categorical cluster membership due to clustering of existing feature vectors in the feature space.

II. 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 causing local variation and the individual loses his/her balance by raising the arms. Research shows that the electromyography (EMG) signal occurs before the action [3], [6]. Studies have also documented the effects local variations in EMG activity during a variety of motor tasks and postural adjustments [10] and general decline of adaptive capabilities [12]. In [13], 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.

III. MULTIVARIATE ANALYSIS OF VISUALLY-SIMILAR MOTIONS

The supervised clustering of feature vectors¹ of all motions gives the distribution of similar motions in different clusters. As per our hypothesis, due to local variation in performance, similar motions may lie in different clusters. To test this hypothesis, we consider the multivariate analysis of variance on the quantitative attributes of all trials of similar motion, say D , based on the clustering results of feature vectors of all motions. That means, for the analysis of variance, an independent variable is represented by the cluster membership and dependent variables are represented by the quantitative attributes. In section V, we see the quantitative attributes and results of multivariate analysis of variance for the “*raise-arm*” experiment.

Let the number of trials for the motion D present in cluster i be n_i , while c represent the number of clusters containing trials of motion D ; this gives $\sum n_i = N$, where N is the total number of trials for the motion D . On having P_{ij} as a vector of attributes for trial j in cluster i , we get \bar{p}_{i*} as a mean vector of attributes for corresponding cluster i and further, grand mean vector of attributes $\bar{p}_{**} = \sum_i \sum_j P_{ij}/N$. Then, according to multivariate analysis, we define *total sum of squares and cross products* $q \times q$ matrix that involves comparing the vectors of attributes for the individual trial from all clusters to the grand mean vector of attributes as follows,

$$T = \sum_{i=1}^c \sum_{j=1}^{n_i} (P_{ij} - \bar{p}_{**})(P_{ij} - \bar{p}_{**})' \quad (1)$$

The $(k, l)^{th}$ element of T is given by,

$$T_{k,l} = \sum_{i=1}^c \sum_{j=1}^{n_i} (P_{ijk} - \bar{p}_{**k})(P_{ijl} - \bar{p}_{**l})' \quad (2)$$

For $k = l$, this is the total sum of squares for attribute k , and measures the total variation in the k^{th} attribute. For $k \neq l$, this is the total cross product between attributes k and l , and measures the dependence or co-variance between variables k and l across all of the clusters.

We can partition the matrix T as the sum of two matrices, where first partition is the matrix of squares and cross products of deviations of vectors of attributes from their corresponding cluster’s mean vector of attributes (“**within**”). And second partition is the matrix of squares and cross products of

deviations of mean vectors of attributes of all clusters from grand mean vector of attributes (“**between**”). Thus,

$$\begin{aligned} T &= \sum_{i=1}^c \sum_{j=1}^{n_i} (P_{ij} - \bar{p}_{**})(P_{ij} - \bar{p}_{**})' \\ T &= \sum_{i=1}^c \sum_{j=1}^{n_i} \{(P_{ij} - \bar{p}_{i*}) + (\bar{p}_{i*} - \bar{p}_{**})\} \\ &\quad \{(P_{ij} - \bar{p}_{i*}) + (\bar{p}_{i*} - \bar{p}_{**})\}' \\ T &= \underbrace{\sum_{i=1}^c \sum_{j=1}^{n_i} (P_{ij} - \bar{p}_{i*})(P_{ij} - \bar{p}_{i*})'}_{\text{within}(E)} \\ &\quad + \underbrace{\sum_{i=1}^c n_i (\bar{p}_{i*} - \bar{p}_{**})(\bar{p}_{i*} - \bar{p}_{**})'}_{\text{between}(H)} \end{aligned} \quad (3)$$

where matrix “**E**” represents within-clusters sum of squares and cross products matrix and matrix “**H**” represents between-clusters sum of squares and cross products matrix. We need these two matrices to calculate Wilks’ lambda that can be used as a statistical test in multivariate analysis of variance to investigate the differences between the means of identified groups of similar trials on a combination of dependent attributes. Using the terms from Equation 3, we get Wilks’ lambda as follows,

$$\text{Wilks' lambda} = \frac{|E|}{|H + E|} \quad (4)$$

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 attributes 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 clusters and minimum separation within the clusters with respect to the entire set of quantitative attributes. Thus, we could reject the null hypothesis if Wilk’s lambda is small (close to zero) because there is a significant difference between the set of means of attributes among the clusters. Also, in multivariate analysis of variance, Wilks’ 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 value of F indicates greater differences in the groups and rejection of null hypothesis.

A. Canonical Analysis

We consider canonical analysis, wherein we look for the linear combination of the original attributes that has the largest separation between clusters. On eigen-decomposing the matrix HE^{-1} we get coefficients for the *canonical variables* in the form of eigen vectors. On projecting the original attributes of trials on the eigenvectors of HE^{-1} , we obtain canonical

¹As discussed in Section I, there are several approaches to generate representative feature vectors for the human motions based on joint movements and muscular activities. Feature extraction technique is not the main objective of this paper.

variables that represent the maximum separation between clusters.

Thus, in canonical analysis, we analyze the relationship of a set of quantitative attributes that represent local variations in visually-similar motions to a clustering of motions based on given feature vectors.

B. Numerical Example

The following example of multivariate analysis of variance (shown in Table I) compares the 3 similar motions in Cluster 1 with another 3 similar motions in Cluster 2 on the given two attributes for the similar kind of motions. The vectors of means and standard deviation for each cluster along with grand mean and standard deviation are appended in Table I.

TABLE I
EXAMPLE FOR ILLUSTRATING THE MULTIVARIATE ANALYSIS OF VARIANCE BETWEEN THE ATTRIBUTES OF TWO GROUPS.

Cluster 1			Cluster 2		
	Att1	Att2		Att1	Att2
M_1	50	22	M_4	7	17
M_2	56	22	M_5	12	19
M_3	58	21	M_6	23	25
mean	54.67	21.67	mean	14	20.33
std	4.16	0.57	std	8.18	4.16
grand mean	Att1 = 34.33, Att2 = 21				
grand std	Att1 = 23.02, Att2 = 2.75				

The total sum of squares and cross product matrix T is;

$$T = \begin{bmatrix} 2649.3 & 146 \\ 146 & 38 \end{bmatrix}$$

To follow, between-clusters sum of squares and cross products matrix H ,

$$H = \begin{bmatrix} 2480.67 & 81.33 \\ 81.33 & 2.67 \end{bmatrix}$$

and,

$$E = \begin{bmatrix} 168.67 & 64.67 \\ 64.67 & 35.33 \end{bmatrix}$$

The corresponding degree of freedom for matrix H , E , and T is given by $df1 = c - 1 = 1$, $df2 = N - c = 4$, and $df_{total} = df1 + df2 = N - 1 = 5$. The corresponding Wilks' lambda for testing the significance difference between means of attributes of two groups is given by,

$$\Lambda = \frac{|E|}{|T|} = \frac{1777.78}{79358.67} = 0.0224 \quad (5)$$

As Wilk's lambda is close to zero with probability $p = 0.003$, there is a significant difference at 0.05 level between the set of means of attributes among the clusters/groups.

Then the corresponding F-value, for this particular case for $q = 2$ and $c = 2$, is given by using equations in Appendix A,

$$n_1 = 2 \text{ and } n_2 = 6 \quad (6)$$

and finally,

$$F = \left(\frac{1 - 0.0224^{\frac{1}{2}}}{0.0224^{\frac{1}{2}}} \right) \left(\frac{6}{2} \right) = 17.04 \quad (7)$$

which also suggests that difference between means of attributes among two clusters is significantly different.

We can further get the univariate F ratios for each of the dependent variables i.e. attributes to know their significance in discriminating the similar motions in different groups. The F-value for univariate analysis is given by ratio H/E . For variable 1, the numerator of the univariate F ratio is 2480.67/1.0 (between), and denominator is 168.67/4 (within) yielding an F ratio of 58.83 with $p = 0.0016$ making it significantly different across two clusters. Similarly, for variable 2, the numerator of the univariate F ratio is 2.67/1.0 (between), and denominator is 35.33/4 (within) yielding an F ratio of 0.3 with $p = 0.62$ which leads to no significant difference between means of attribute 2 across both clusters.

This suggests that, cluster analysis on the feature vectors that separates similar motions M_{1-3} from M_{4-6} in two different clusters have significantly different quantitative attribute "Att1". and has no effect by other quantitative attribute "Att2".

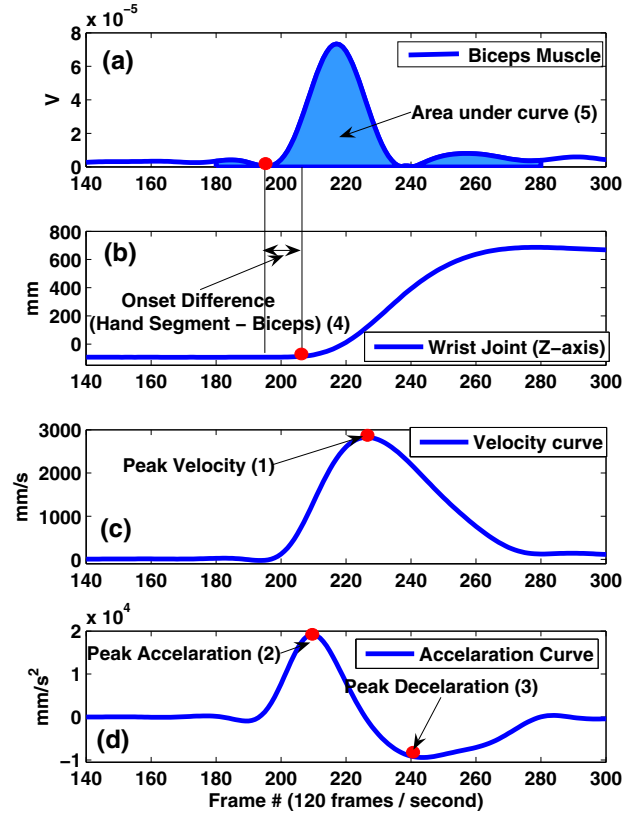


Fig. 1. Quantitative attributes between biceps and wrist for illustration. (For full set of attributes refer Table II.)

IV. EXPERIMENTAL PLATFORM

A. Motion capture acquisition and analysis

The motions from 22 participants were captured in the Motion Capture Lab equipped with 16 cameras (Vicon Systems). Data from all cameras were acquired at 120 frames per second. The details of this procedure are discussed in [4].

B. EMG acquisition and analysis

EMG Ag-CI 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 brachii (biceps), triceps brachii (triceps), flexor carpi radialis (flexor), and extensor carpi radialis muscles (extensor). 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.

C. Integrating motion capture and EMG data

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.

TABLE II
QUANTITATIVE ATTRIBUTES FOR EXPERIMENT “RAISE-ARM” FROM
FIGURE 1.

#	Explanation of Parameter
1	Peak Velocity.
2	Peak Acceleration.
3	Peak Deceleration.
4	Onset time difference between hand segment and biceps muscle.
5	Area under curve for biceps muscle while jump.
6, 7	Onset time difference between hand segment and triceps muscle. Area under curve for triceps muscle while jump. (not shown)
8, 9	Onset time difference between hand segment and flexor muscle. Area under curve for flexor muscle while jump. (not shown)
10, 11	Onset time difference between hand segment and extensor muscle. Area under curve for extensor muscle while jump. (not shown)

V. PERFORMANCE EVALUATION

In this section, we evaluate the effect of local variations in the multiple trials of “raise-arm” motion performed by different participants.

A. Visually-similar motion: “Raise-Arm”

Table II shows the list of quantitative attributes corresponding to the “Raise-arm” experiment, which are measured from the synchronous time series of joint movements and muscular activities. For illustration, Figure 1(a) shows the biceps muscle activity during *raise-arm* activity and Figure 1(b) shows the hand segment (i.e. wrist joint) movement along *Z*-axis. Figure

1(c) and Figure 1(d) are the velocity and acceleration curve respectively for the wrist movement. First five attributes in Table II are marked in Figure 1, while other attributes can be extracted similarly from the respective muscles’ activity. In the process of analyzing this *raise-arm* activity, we conducted the experiment on 22 participants, with each one repeating 10 times (i.e. 220 trials). We extracted quantitative attributes described in Table II from all these visually-similar trials.

B. Feature Vectors

The entire motion database consisted of different types of human activities ‘raising-arm’, ‘walking’, ‘stepping’, ‘jumping’, ‘sitting’, ‘catching ball’, ‘throwing ball’, and ‘raising arm with weighted objects’. In [4], we proposed feature extraction technique for joint movements and muscular activities. The preliminary features for joint movements and muscular activities were extracted using weighted singular value decomposition and Integral Absolute value respectively, across sliding window for each motion. On concatenating these features for each window, the corresponding motion was represented by a set of combined feature vectors. Fuzzy clustering on combined feature vectors for all motions gave the range for degree of membership for each fuzzy cluster, which was considered as the final feature vector for the motion. The advantage of this approach from our analysis perspective is that by varying the number of fuzzy clusters we can have different configurations of final feature vectors for the same set of motions that considers,

- only joint movements,
- only muscular activities, or
- both joint movements and muscular activities.

C. Analytical Results

The traditional clustering of final feature vectors for all motions may give us one or more clusters containing *raise-arm* motions. For multivariate analysis of variance, the categorical cluster identifiers containing raise-arm motions is considered as an independent variable, while 11 quantitative attributes from Section V-A are considered as the set of dependent variables. The minor number of similar trials (less than 5% of total similar trials) that are present in a different cluster other than the clusters containing majority of similar trials are neglected as outliers.

Table III shows the results of multivariate analysis of variance for all three combinations of feature vectors and for varying cluster numbers (3 – 20) used in fuzzy c-means clustering for generating final feature vectors (from Section V-B). As seen from Table III, for almost all entries, *F*-value (with $p < 0.001$) for feature vectors that consider both joint movements and muscular activities are mostly greater than only joint movements and muscular activities feature vectors. This confirms that, the variations in quantitative attributes of the “raise-arm” activity has a more significant effect on the clustering with integrated features of joint movements and muscular activities than the clustering with separate features. For illustration, we consider the grouping of all three kinds

TABLE III
RESULT OF MULTIVARIATE ANALYSIS OF VARIANCE FOR ALL THREE TYPES OF FEATURE VECTORS REPRESENTING HAND-SPECIFIC EXPERIMENT “raise-arm”.

	Joint Movement			Muscular Activity			Both		
	df	Wilk's λ	F	df	Wilk's λ	F	df	Wilk's λ	F
3	2, 198	0.53	6.47***	2, 210	0.24	18.88***	2, 198	0.28	15.05***
4	3, 202	0.41	6.08*	2, 203	0.33	12.86*	2, 196	0.32	12.90***
5	3, 202	0.46	5.21*	2, 193	0.46	7.83*	2, 206	0.41	10.15***
6	2, 182	0.60	4.54*	2, 191	0.53	6.13***	2, 203	0.32	13.32***
7	2, 191	0.52	6.33**	3, 209	0.52	4.39*	2, 204	0.40	10.26***
8	3, 204	0.45	5.40***	3, 197	0.49	4.58***	2, 197	0.39	10.35***
9	2, 181	0.59	4.76**	3, 194	0.47	4.86**	2, 187	0.38	10.02***
10	2, 177	0.69	3.14*	1, 192	0.53	14.60***	2, 210	0.65	4.35***
11	2, 193	0.67	3.64*	2, 173	0.59	4.51***	2, 210	0.70	3.58***
12	1, 189	0.82	3.56***	3, 190	0.52	4.00**	3, 200	0.42	5.78***
13	2, 197	0.61	4.71***	1, 159	0.80	3.41***	3, 200	0.38	6.61***
14	2, 184	0.56	5.38***	3, 198	0.56	3.70***	2, 206	0.65	4.21***
15	2, 183	0.57	5.19***	2, 198	0.62	4.59**	3, 208	0.39	6.74***
16	2, 204	0.67	3.98***	2, 190	0.63	4.32*	3, 208	0.41	6.26***
17	1, 191	0.79	4.33***	2, 186	0.61	4.54***	2, 203	0.65	4.25***
18	1, 186	0.84	3.05***	2, 192	0.63	4.32***	2, 208	0.67	3.97***
19	2, 188	0.62	4.40**	2, 186	0.65	3.92**	2, 207	0.55	6.17***
20	2, 207	0.55	6.26***	2, 201	0.78	2.34*	3, 207	0.45	5.53***

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE IV
UNIVARIATE ONE-WAY ANALYSIS FOR 11 QUANTITATIVE ATTRIBUTES OF HAND-SPECIFIC EXPERIMENT (raise-arm) FOR THREE TYPES OF FEATURE VECTORS GENERATED BY FUZZY 6-MEANS CLUSTERING.

Feature Vectors	F-value										
	1	2	3	4	5	6	7	8	9	10	11
Joint Movement	2.41	2.05	2.52	0.63	1.19	0.54	1.94	2.28	3.86	1.80	5.22
Muscular Activity	26.45	23.07	8.48	1.33	11.80	3.74	4.05	6.99	3.83	5.28	26.67
Both	26.21	38.02	50.72	1.31	23.56	13.44	7.02	12.77	2.84	42.91	41.84

of feature vectors generated by the fuzzy 6-means clustering (corresponding row is shaded in Table III). It can be seen that there is a significant difference in the three clusters due to integrated feature vectors (Wilks' lambda = 0.32, $F = 13.32$, 2 and 203 df, $p < 0.001$). To investigate the sources of these differences, we conduct one-way (univariate) analysis of variance (ANOVA) on all dependent attributes to see which attributes contributes for the significant differences between the three clusters of similar motion (raise-arm). Table IV shows the F-value for all three types of feature vectors, and as we can notice, the F-value for almost all attributes is larger while considering integrated feature vectors. This shows that the clustering of the integrated feature vectors has a significant effect due to differences between similar motions with respect to extracted quantitative attributes.

D. Canonical Analysis

We conduct a canonical analysis for the same three combinations of feature vectors that are generated by the fuzzy 6-means clustering. In canonical analysis, we find a new set of variables called “canonical variables” that are linear combinations of the original variables such that cluster differences are maximized. To achieve maximum discrimination, we need maximum separation between the clusters and minimum separation within the clusters. For that we take the ratio of between-clusters sum of squares and cross-products matrix (H) to the within-clusters sum of squares and cross-products matrix (E) from respective multivariate analysis of variance

(as seen in Section III). The eigen decomposition of HE^{-1} gives the coefficients of the linear combination of the original variables in the form of eigenvectors. Thus, on projecting original data-set vector (i.e. vector of quantitative attributes or original variables) on the eigenvectors of HE^{-1} we get canonical variables that represent the maximum separation between clusters. Figure 2 (a), (b), and (c) shows the grouped scatter plot of the first two canonical variables with respect to joint movement feature vectors, muscular activity feature vectors, and integrated feature vectors respectively. These plots have more separation between groups than the respective grouped scatter plots of any pair of original attributes. We can observe that, among these three plots, Figure 2(c) that corresponds to the grouped scatter plot with respect to the feature vectors that integrates both joint movements and muscular activities shows better discrimination across groups in canonical space. In Figure 2 (c), we roughly represent the virtual, approximate boundaries indicating three groups that shows maximum discrimination between the groups in the defined canonical space. The first canonical variable separates trials within Group 2 (that have low values of c_1) from other two groups. The second canonical variable, c_2 , reveals some separation between Group 1 and Group 3.

VI. CONCLUSIONS

In this paper, we proposed a multivariate analysis technique that evaluates the local variations in visually-similarly motions by extracting the quantitative attributes from the multiple

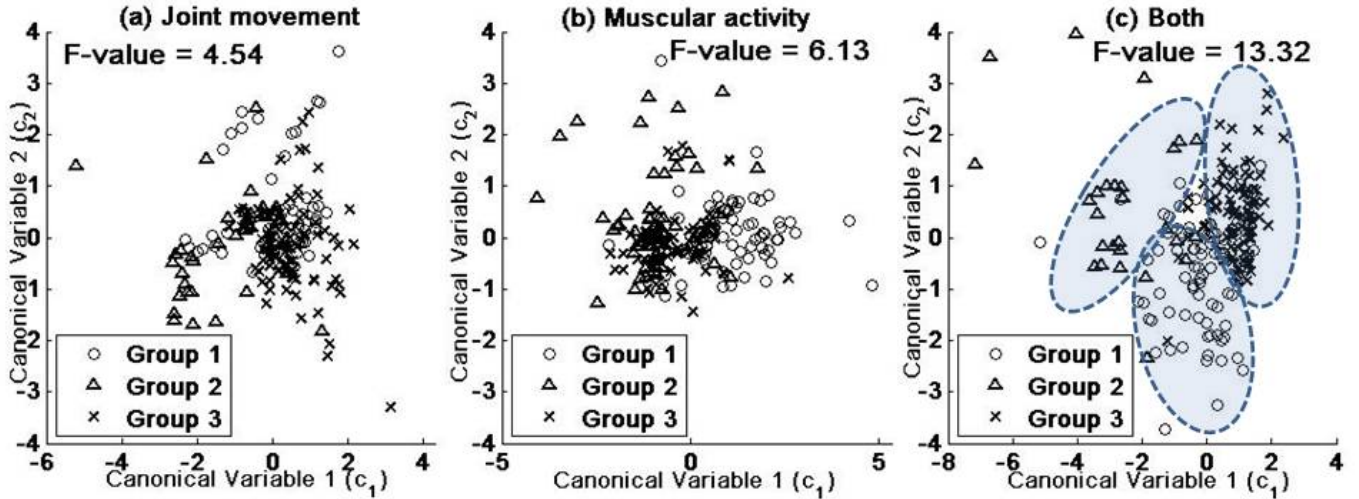


Fig. 2. Grouped scatter plot of the first two canonical variables with respect to motion capture feature vectors (a), EMG feature vectors (b), and combined feature vectors (c) representing hand-specific experiment “raise-arm”.

data streams of joint movements and muscular activities. The cluster membership resulting from clustering the given feature vectors of all motions was used as independent variable in multi-variate analysis of variance (manova), and visually-similar motions’ quantitative attributes were treated as multiple dependent variables. The effect of local variations in the form of change in quantitative attributes for the “raise-arm” activity was significant on the clustering of integrated features of joint movements and muscular activities. The univariate F-value for almost all quantitative attributes for the “raise-arm” activity were larger when cluster membership due to clustering of integrated feature vectors was used as an independent variable as compared to the separate feature vectors. Further, on conducting canonical analysis for all three combinations of the feature vectors, we achieved maximum discrimination across clusters (i.e. maximum separation between clusters and minimum separation within clusters) in the canonical space for the integrated feature vectors as compared to separate feature vectors for joint movements and muscular activities.

This baseline study forms the starting point to evaluate the local variations in the visually-similar motions that are considerably important in analyzing body sensor data in applications like assistive-living environment and rehabilitations.

REFERENCES

- [1] A. D. Boca and D. Park. Myoelectric signal recognition using fuzzy clustering and artificial neural networks in real time. In *IEEE International Conference on Neural Networks and IEEE World Congress on Computational Intelligence*, volume 5, pages 3098–3103, Orlando, FL, USA, 1994.
- [2] F. H. Chan, Y.-S. Yang, F.K.Lam, Y.-T. Zhang, and P. Parker. Fuzzy EMG classification for prosthesis control. *IEEE Transactions on Rehabilitation Engineering*, 8(3):305–311, September 2000.
- [3] 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.
- [4] G.N.Pradhan, N. Engineer, M. Nadin, and B. Prabhakaran. Integration of motion capture and EMG data for classifying the human motions. In *ICDE Workshop on Ambient Intelligence, Media, and Sensing*, April 2007.

- [5] V. Gupta, S. Suryanarayanan, and N. Reddy. Fractal analysis of surface EMG signals from the biceps. *International Journal of Medical Informatics*, 45(3):185–192, July 1997.
- [6] 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.
- [7] C. Li and B. Prabhakaran. A similarity measure for motion stream segmentation and recognition. In *Proc. MDM/KDD, The sixth International Workshop on Multimedia Data Mining*, Chicago, IL USA, August 2005.
- [8] C. Li, G. Pradhan, S. Zheng, and B. Prabhakaran. Indexing of variable length multi-attribute motion data. In *Proc. ACM - MMDB*, Washington, DC, USA, November 2004.
- [9] F. Liu, Y. Zhuang, F. Wu, and Y. Pan. 3D motion retrieval with motion index tree. *Computer Vision and Image Understanding*, 92:265–284, June 2003.
- [10] I. Melzer, N. Benjuya, and J. Kaplanski. Age-related changes of postural control: effect of cognitive tasks. *Gerontology*, 47(4):189–194, 2001.
- [11] M. Muller, T. Roder, and M. Clausen. Efficient content-based retrieval of motion capture data. *ACM Transactions on Graphics (TOG)*, 24:677–685, 2005.
- [12] M. Nadin. *Mind - Anticipation and Chaos*. Belser Presse, 1991.
- [13] G. Pradhan, N. Engineer, M. Nadin, and B. 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, Nov. 2007.
- [14] G. N. Pradhan, C. Li, and B. Prabhakaran. Hierarchical indexing structure for 3d human motions. In *Int’l Proceedings of 2007 ACM Multimedia Modeling Conference*, pages 386–396, January 2007.

APPENDIX

To calculate F it is necessary to compute set of functions from q (number of attributes), c (number of clusters), and N (total number of trials in all clusters),

$$s = \sqrt{\frac{q^2(c-1)^2 - 4}{q^2 + (c-1)^2 - 5}} \quad (8)$$

$$n_1 = q(c-1) \quad (9)$$

$$n_2 = s \left[(N-1) - \frac{q + (c-1) + 1}{2} \right] - \frac{q(c-1) - 2}{2} \quad (10)$$

Now let,

$$y = \Lambda^{\frac{1}{s}} \quad (11)$$

and finally,

$$F = \left(\frac{1-y}{y} \right) \left(\frac{n_2}{n_1} \right) \quad (12)$$