Cluster Dominance Analysis of Strength Training Motion Characteristics

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***Abstract*—This paper presents an approach to analyze clusters as a means to determine the characteristics of strength training motion patterns. The proposed method emphasizes the observation of dominance sequences within clusters and is reinforced by the formation of specific characteristics within each cluster. Data collection is performed using video-guided strength training exercises equipped with 1 kg dumbbells and recorded by a sensor embedded in smartwatches. The analysis method involves applying the concept of density affinity, which calculates the density ratio of clusters to the recognized motions. Subsequently, the dominance sequence is observed to identify which clusters exhibit distinct characteristics, ultimately determining the intended motions. The research findings demonstrate the potential for further investigation into a more comprehensive understanding of motion patterns, leading to the development of models that can be integrated into mobile devices or smartwatches.**

Keywords—cluster analysis, density affinity, motion patterns, smartwatch, strength training motion

I. Introduction

The development of mobile applications for Human Activity Recognition (HAR) is a current trend in the digital era and is widely used for suggesting overall health activities, including for seniors [1]. For instance, walking patterns throughout the day can be used to calculate calorie expenditure and ultimately guide dietary recommendations for individuals. The commonly used technique involves machine learning with the detection of sensor values recognized from gadgets, such as motion speed, rotational position, and gravity [2]. One of the main challenges in HAR is the potential overlap of sensor values between different motions [3], particularly when considering individual data points without considering their sequential nature. For example, in the case of weightlifting motions like overhead press and overhead triceps exercises using a dumbbell in a relatively static position, such as sitting.

Based on the aforementioned challenges, this paper presents an effort to conduct cluster analysis to determine which sensor values play a role in a weightlifting motion pattern. The primary contribution of this paper is to demonstrate the characteristics of sensor values within a cluster and their relevance to the similarity of weightlifting motion patterns. Through this analysis, it is hoped that the validation of machine learning models for recognizing weightlifting motions can be facilitated.

II. Method

The cluster analysis technique considers affinity, which refers to the relationship between clusters by considering the overlapped features within analyzed clusters. The proposed technique in this paper combines the following ideas: 1) dimension reduction, ensuring that only relevant features play a role in the cluster formation [4], and 2) cluster affinity, which favors proximity that can be propagated within certain boundaries until a certain number of clusters are formed [5].

The concept of measuring affinity is employed to assess the closeness of the cluster characteristics formed through k-means. Two reasons support this approach: 1) the number of clusters is pre-defined based on the number of motions presented in the weightlifting tutorial videos, and 2) the assumption that each cluster formed by the k-means algorithm possesses characteristics aligned with the potential of its constituent features [6].

Hence, the main workflow steps proposed in this research are illustrated in Figure 1. The dataset used was collected from 25 students using smartwatch devices, equipped with 1 kg dumbbells. The choice of the dumbbells' weight is based on the instruction as recommended in the video [7], with one repetition maximum (rm) for weight training [8]. The use of students is assumed to provide general characteristics that can be applied to all age categories. From the collected data, a feature selection process is performed using Pearson Correlation, as discussed in [9]. The selected features are then used for cluster formation using the k-means algorithm, with a total of 9 clusters as per the weightlifting tutorial videos [7].

After the clusters are formed, the density affinity ratio is observed (see Formula 1) to examine the dominance sequence of clusters when a particular motion is performed. This observation aims to analyze the assumption that there is a significant overlap of data points and to understand the cluster characteristics of those overlapping data points.

$$\text{affinity ratio} = \frac{\text{total number of identified motion in cluster x}}{\text{total member of instances in cluster x}} \text{ x } 100\% \qquad (1)$$

In the final stage, the characteristics of each cluster are extracted by calculating the weights of each feature within the cluster. The weight calculation is performed by taking the average value of each feature included in the cluster set as given in Formula 2. With the establishment of the characteristics of each cluster, it becomes possible to identify which features have a high impact on each strength training motion present in the dataset. Furthermore, by observing the dominance sequence of clusters, it is possible to propose a focus on more general characteristics for motion recognition. This would be highly advantageous as a valid alternative during the development of machine learning models, aiming to avoid potential overfitting on this specific dataset [9].

$$\text{feature's weight in cluster x} = \frac{\text{total sum of feature's value}}{\text{total number of instances}} \quad (2)$$

III. Result and Discussion

A. Cluster Affinity

The set of sensor features captured using a smartwatch device (on the right-hand motion) along the x, y, and z axes includes an accelerometer, magnetometer, gyroscope, linear accelerometer, gravity, Euler angles, (inverse) quaternion, and relative orientation. There are 29 features (32,296 data rows), with an additional axis, w, for (inverse) quaternion. Using Pearson Correlation based on the accelerometer, 11 influential features were obtained as follows: accelerometer_x, linear_accelerometer_x, gravity_x, euler_x, euler_z, quaternion_x, quaternion_z, inverse_quaternion_x, inverse_quaternion_x, relative_orientation_z, and magnetometer_x [9]. These selected 11 features serve as the basis for the formation of subsequent clusters. By employing the k-means algorithm, nine clusters were formed, and the distribution of motion labels is presented in the confusion matrix in Table I.

To delve deeper into the case in this paper, an example of the overhead press (first row) and overhead triceps (fourth row) with highly similar motions is described (see Fig. 2). Both motions exhibit the highest density affinity in c2 (green-shaded) and c6 (blue-shaded). This indicates a significant overlap in features between the two motions. However, it can also be observed that the overhead press tends to be clustered in c3 (yellow-shaded), while the overhead triceps primarily cluster in c1 as the third-density affinity. Hence, there are distinguishing characteristics within specific time ranges when these motions are performed.

TABLE I. Percentage Distribution of The Clusters' Affinity for Each Detected Motion

% distrib.	c1	c2	c3	c4	c5	c6	c7	c8	c9
overhead press	**6.67**	**25.52**	**16.50**	**15.65**	**4.49**	**16.59**	**11.76**	**2.31**	**0.51**
bicep curls	14.85	24.83	16.03	12.31	11.08	6.63	0.45	6.50	7.32
lateral raise	17.12	28.15	32.07	9.40	1.48	8.37	0.13	1.74	1.54
overhead triceps	**14.36**	**26.46**	**7.99**	**7.66**	**8.61**	**19.97**	**7.26**	**4.87**	**2.82**
diagonal shoulder raise	29.35	26.35	22.36	10.42	1.17	0.57	2.44	5.18	2.14
forward punches	7.70	12.73	24.45	6.20	0.52	35.63	0.84	1.45	10.49
reverse flyes	26.69	13.54	12.25	6.68	24.10	0.53	0.03	16.04	0.15
seated rows	17.02	25.98	14.94	17.75	5.98	0.07	0.00	18.15	0.10
modified skull crushers	10.56	15.81	8.43	7.14	17.26	21.87	5.12	5.25	8.56
all	17.40	21.95	18.91	9.82	6.97	12.19	2.58	6.22	3.96

B. Example of Cluster Dominance

Based on the example in the previous subsection, *i.e.* the overhead press and overhead triceps motions, the differentiating characteristics are found within the third cluster sequence, specifically in c3 and c1. The differentiating characteristics for both motions can be observed in Table II.

TABLE II. Specific Characteristics of Cluster C1 and C3

Clust.	Features	Weights	Clust.	Features	Weights
c1	accelerometer_x	3.10	c3	euler_x	4.11
	gravity_x	3.10		magnetometer_x	1.63
	quaternion_z	0.43		lin.accelerom._x	1.38
	inv.quaternion_z	0.43		quaternion_x	0.70
	quaternion_x	-0.86		inv.quaternion_x	0.70
	inv.quaternion_x	-0.86		rel.orientation_z	0.60
	magnetometer_x	-1.24		euler_z	0.59
	euler_x	-3.99		accelerometer_x	-0.59
	euler_z	0.00		gravity_x	-0.59
	lin.accelerom._x	0.00		quaternion_z	-3.09
	rel.orientation_z	0.00		inv.quaternion_z	-3.09

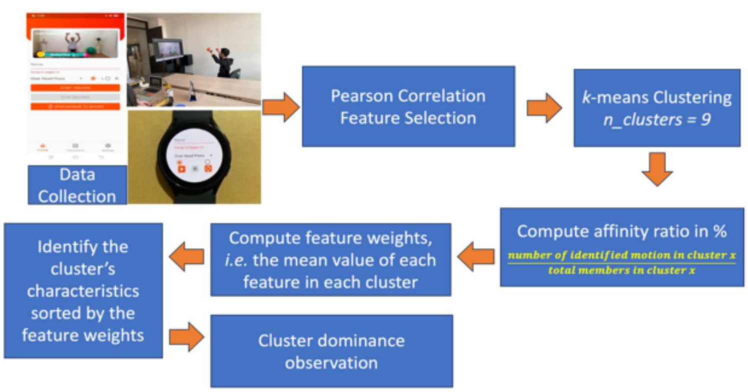

Fig. 1. The methodology to analyze cluster characteristics in strength training exercise motion patterns in this study.

Fig. 2. The compared motions in the example are overhead press (left) and overhead triceps (right). Source: https://www.fitliferegime.com/.

By considering the dominant sequence of clusters, namely c2-c6-c3 for the overhead press motion, and c2-c6-c1 for the overhead triceps motion, it suggests the potential to study specific components within a specific time range. This also indicates the potential use of time series analysis techniques such as recurrent neural networks (RNN) or long-short-term memory (LSTM).

C. Clusters Dominance in Each Motion

Inferring from Table 1, we can follow the clusters' dominance in each motion. This analysis may be important for identifying what type of sensor is specific for determining the detection of a strength motion. The information is summarized in Table III.

TABLE III. CLUSTERS DOMINANCE IN EACH MOTION UP TO THE FOURTH CLUSTER AFFINITY

Motion	Sequence of Clusters
overhead press	c2 - c6 - c3 - c4
bicep curls	c2 - c3 - c1 - c4
lateral raise	c3 - c2 - c1 - c4
overhead triceps	c2 - c6 - c1 - c5
diagonal shoulder raise	c1 - c2 - c9 - c1
forward punches	c6 - c3 - c2 - c1
reverse flyes	c1 - c5 - c8 - c2
seated rows	c2 - c8 - c4 - c1
modified skull crushers	c6 - c5 - c2 - c1

Four motions are dominated by the characteristics in c2, namely overhead press, bicep curls, overhead triceps, and seated rows. The forward punches and modified skull crushers are dominated by the characteristics in c6. The other motions are dominated by c1, *i.e.,* diagonal shoulder raise and reverse flyes, and finally by c3 for lateral raise motion. The characteristics of c1 and c3 are given in Table II. In Table IV, the characteristics of c2 and c6 are shown. Further investigation shows that the total number of instances in c1, c2, c3, and c6 is around 70.45%. This fact suggests that those clusters potentially have the most mixed members.

Compared to the characteristics of c1 and c3 in Table II, the most influential sensors of c2 and c6 are the same, *i.e.*, euler_x and accelerometer_x with variated weights. These suggest the potential of motion uniformity but with specific details. As a consequence, to detect the motion pattern automatically all influential features from the sensors need to be included during the training.

The selected attributes of the clusters in Table II and III show that the attributes on the x and z axes are very dominant. This indicates that the horizontal (x-axis) and the depth (z-axis) motions corresponding to the directions on the device screen are dominant in the series of exercises performed.

TABLE IV. SPECIFIC CHARACTERISTICS OF CLUSTER C2 AND C6

Clust.	Features	Weights	Clust.	Features	Weights
c2	euler_x	2,55	c6	accelerometer_x	81,41
	magnetometer_x	2,37		gravity_x	81,41
	lin.accelerom._x	0,77		quaternion_z	45,44
	quaternion_x	-0,28		inv.quaternion_z	45,44
	inv.quaternion_x	-0,28		rel.orientation_z	16,18
	euler_z	-1,04		euler_z	16,10
	rel.orientation_z	-1,06		quaternion_x	9,74
	quaternion_z	-6,46		inv.quaternion_x	9,74
	inv.quaternion_z	-6,46		euler_x	2,97
	accelerometer_x	-12,52		magnetometer_x	2,55
	gravity_x	-12,52		lin.accelerom._x	0,10

D. Motions' Patterns Visualization

Fig. 3 shows a visualization of the feature value patterns from several motions. The figure shows the first 50 records of the overhead press and overhead triceps accompanied by euler_x and magnetometer_x feature value patterns. These patterns emphasize the findings in the previous section which showed that although the motions are identified by the same influential features, there are some deeper important details to be learned.

IV. CONCLUSION AND FURTHER RESEARCH

The research findings indicate that our approach successfully identifies the dominance sequence of clusters along with the characteristics of each cluster. Based on the assumption that the identified characteristics stem from differences in motion patterns over a specific time range, machine learning based on time series analysis is expected to have an impact on motion recognition. As a follow-up to this research, a more in-depth exploration of motion patterns will be conducted to develop a model that can be integrated into mobile devices or smartwatches. Another noticeable thing was that the x and z axes proved to require more attention than the y axes. This may be related to the limited rotation of the hand and arm making motions about the same axis.

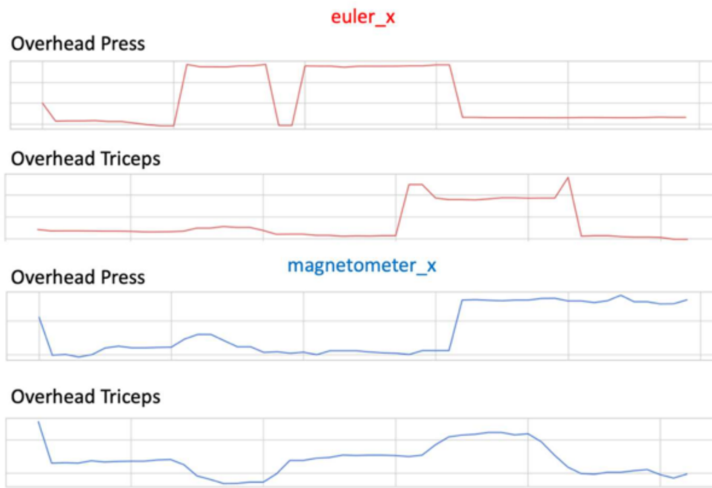

Fig. 3. Visualization of feature value patterns from the first 50 records of the overhead press and overhead triceps. Each motion repetition lasts approximately 7-8 seconds. To ensure the capture of all repetitions, 7 lines of sensor records are stored in each second.

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