Time Domain Cluster Analysis of Human Activity Using Triaxial Accelerometer Data

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***Abstract*—This paper presents a cluster analysis of raw triaxial accelerometer data aquired from various human physical activities as well as simulated falls. Clustering was performed using K Means, Gaussian Mixed Model and Fuzzy C-Means clustering. In our analysis we focused on two problems: the first clustering problem was based on activity recognition and differentiation from simulated human falls, while the other problem focused on distinction between single jerk events (e.g. jumping, falling) and continuous activity signals (e.g. running, walking).**

***Index Terms*—signal processing, accelerometer, clustering, biomedical engineering, data analysis**

I. Introduction

In recent times Human Activity Recognition (HAR) has become a research area that attracted a great deal of interest, especially in biomedicine and biomedical engineering. One of the reasons for the increased popularity of the area is the availability of data: today user data are available through many devices, such as smartphones and their apps, portable sensors, wristbands, smartwatches, etc. for real-time analysis. With the surge of biomedical data science, more and more artificial intelligence (AI) techniques are employed to discover knowledge, unveil latent data behavior, generate new insight, and seek optimal strategies in decision making. Different AI methods have been proposed and developed in almost all different biomedical data science fields that range from healthcare analytics, electronic medical records (EMRs) data automation, early disease diagnosis, drug discovery, single-cell RNA sequencing and COVID research (1). The statistical analysis of biological data acquired from various sensors can provide useful information for a wide range of medical applications, one of them being elderly care.

Falls among the elderly population represent a significant challenge for public healthcare systems, especially with the growing elderly population in developed nations. According to data from World Health Organization (WHO), falls rank as the second most common cause of unintentional injury-related fatalities on a global scale (2). Moreover, it is also important to stress the fact that individuals aged 60 and above experience the highest incidence of fatal falls. As reported in "United Nations World Population Ageing 2020 Highlights", the living arrangements of elderly have changed, increasing the number of people living independently (3). Living on one's own at this age can definitely put people at increased risk even when performing daily routine activities due to decline in motor skills.

Fall detection as a research area has attracted interest in recent times since users generate real time data from portable medical devices, which can be wearable (attached to the subject's body) or non-wearable (e.g. cameras, pressure sensors, ultrasound or optical motion sensors). Methods based on wearable sensors offer advantages in terms of cost, size, weight, power consumption, ease of use and portability.

Since machine learning and deep learning-based approach tend to be more popular areas of focus, cluster-based analysis of accelerometer data remains a fairly scarce research area. However, some authors have explored clustering of such data, whether solely accelerometer data (4) or as a sensor fusion analysis (5). Since we have already performed supervised machine learning analysis for human activity recognition in our previous research (6) (7), the use of unsupervised methods such as cluster analysis could provide new insights for further research of this particular signal processing problem.

II. Materials and Methods

A. Data Acquisition

The data used for this analysis consists of two merged time series datasets, *UniZg activ2* dataset and *UniZgFall1* dataset. The acquisition of signals for both datasets was conducted on the premises of University of Zagreb, Faculty of Electrical Engineering and Computing (8) (9). The acquisition of data for both datasets used in this analysis was conducted using wearable Shimmer3 Inertial Measurement Unite (IMU) sensors. Shimmer3 is a battery powered wireless sensor node that contains multiple sensors. Each sensor node consists of multiple micro-electromechanical systems (MEMS), which include two 3D accelerometers (a Wide Range and a Low Noise Accelerometer), a 3D magnetometer, a 3D gyroscope, a barometric altimeter and a temperature sensor, as well as a Bluetooth device which enables data streaming in real time.

1) UniZg activ2 dataset: This dataset contains human activity signal data recorded using the aforementioned Shimmer3 inertial measurement unit (IMU), using its built-in triaxial wide range accelerometer with a range of +/- 8g, triaxial magnetometer and triaxial gyroscope sensors at a sampling frequency f_s of 204.8 Hz. Only accelerometer data was used for this analysis. 19 subjects aged 15 to 44 wore the device attached to their waist with a Velcro belt and performed nine activities of daily living ("sitting down", "walking", "standing up from sitting", "standing up from lying", "walking downstairs", "walking upstairs", "lying down", "running" and "jumping") and three simulated falls on a 2 cm thick tatami mat ("falling forward", "falling backward" and "falling sideways"). That brings to a total of 866 signals describing 12 classes for prediction. The waveforms of accelerometer signals describing each activity are presented in Figure 1. For the purposes of this research, we grouped all three falling activities as one activity, "falling".

2) UniZgFall1 dataset: Another dataset used in our research contains human simulated fall data of 39 healthy subjects who participated voluntarily, 12 of which were females and 27 males. All participants gave their informed consent before participating in the study. While recording activities in this study we used a Wide Range Accelerometer with a measurement range set to ±8 g, a magnetometer, a gyroscope, as mentioned in the earlier research by Šeketa et al. (9), with an additional barometric altimeter. Recordings of barometric altimeter, magnetometer and gyroscope were not used for the purpose of this analysis. All sensors were sampled at a frequency f_s of 201 Hz.

The subjects wore three Shimmer3 devices. Two of them were placed above the navel, and the third on subjects' right hip, at the height of where one would wear a belt. Despite being provided with verbal guidance, it was essential for the participants to attach the sensors themselves. This approach aimed to enhance the reliability of the recorded data, as real-world users of wearable fall detection systems should ideally be capable of placing the sensor without the need for professional assistance. Following the placement of the sensor nodes, the subjects performed five distinct simulated falls.

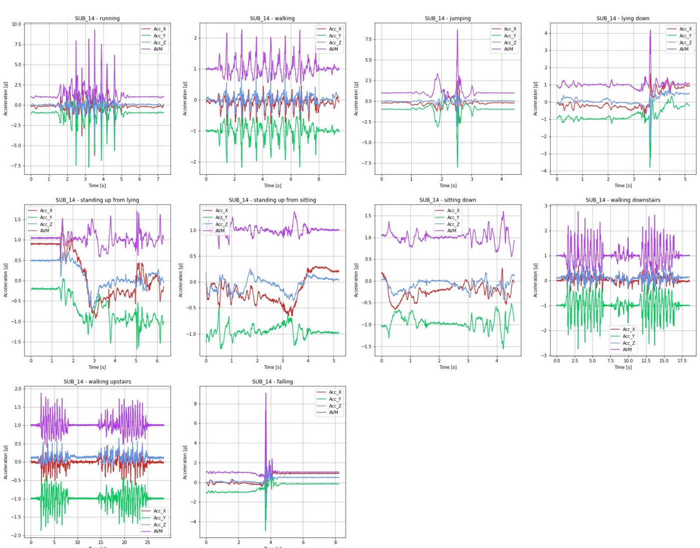

Fig. 1. Visualization of raw accelerometer signals of physical activities - UniZg activ2 dataset, in sequence from left to right: running, walking, jumping, lying down, standing up from lying, standing up from sitting, sitting down, walking downstairs, walking upstairs, falling

TABLE I
PHYSICAL ACTIVITY TARGET CLUSTER BELONGING

Activity	Label 1	Label 2
Running	ADL	Continuous activity
Walking	ADL	Continuous activity
Jumping	ADL	Single event
Lying down	ADL	Single event
Sitting down	ADL	Single event
Standing up from lying	ADL	Single event
Standing up from sitting	ADL	Single event
Walking downstairs	ADL	Continuous activity
Walking upstairs	ADL	Continuous activity
Falling	Fall	Single event

B. Data Preprocessing

The cluster analysis involved two types of clustering using time domain features: by activity type, involving two categories ("Activity of daily living, ADL" and "Fall") and by signal event type based on continuity, also involving two categories ("Continuous activity" and "Single event"). Labeling of physical activities in both cases is shown in Table 1.

Data clustering consisted of analysis of four different accelerometer signals: accelerometer signal data in all 3 axes (X, Y and Z), and acceleration vector magnitude (AVM):

$$AVM(n) = \sqrt{a_x^2(n) + a_y^2(n) + a_z^2(n)} \quad (1)$$

where a_x, a_y and a_z represent acceleration values along corresponding axes.

Due to the non-periodic nature of motion signals, the accelerometer data were described using statistical measures of central tendency and dispersion: signal minimum and maximum, range, mean, median, standard deviation, variance, mean absolute deviation (MAD), interquartile range (IQR), skewness, and kurtosis. Apart from above mentioned, two additional features were considered for the feature selection process: signal energy E_s and signal magnitude area SMA, described in equations 2 and 3.

$$E_s = \int_0^T |s(t)|^2 \, dt \quad (2)$$

$$SMA = \frac{1}{T}\int_0^T |x(t) - a_x| + |y(t) - a_y| + |z(t) - a_z| \, dt \quad (3)$$

where $x(t)$, $y(t)$ and $z(t)$ represent the value of signal $s(t)$ along corresponding axes. Offset correction for each axis in equation 3 are represented as a_x, a_y and a_z. A pairplot visualization of each feature's distribution and relationships between two features is shown in Figure 2.

After the initial feature extraction, in order to build simpler and more comprehensible models and increase their performance, feature selection was conducted using various data analysis methods. In this study we used correlation matrices to illustrate the relationships between features or between features and an output (e.g. cluster membership). Through the use of correlation analysis certain features have proven to be redundant, and were therefore removed (e.g. skewness, IQR).

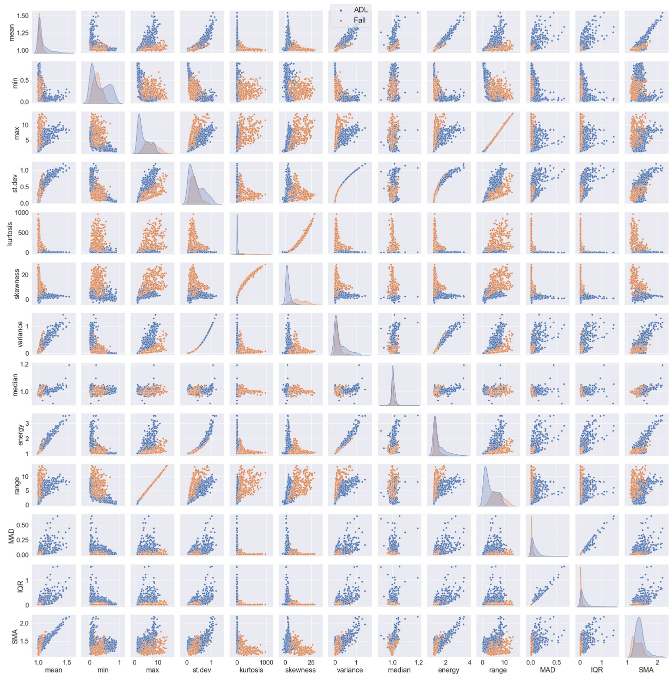

Fig. 2. Pairplot showing feature distribution and relationships between features. Activities of daily living were marked in blue, and falls in orange.

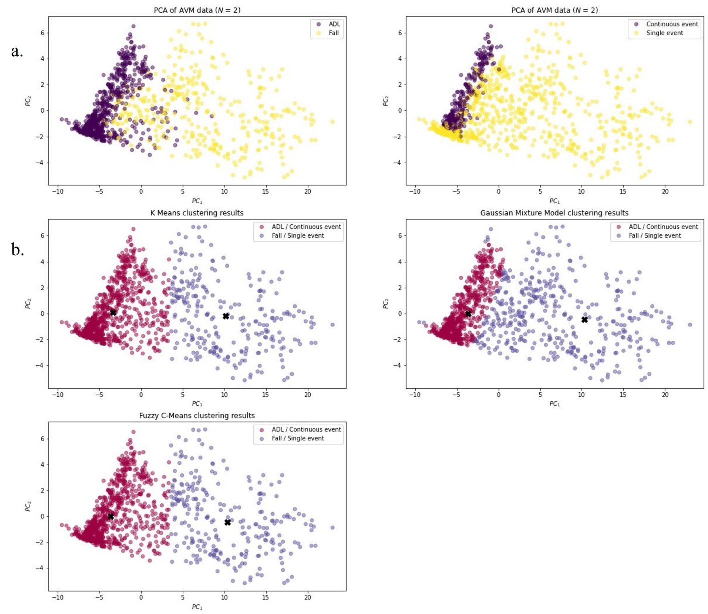

Fig. 3. Visualization of AVM signal data labeled by activity type and event type (a.), and the cluster results using K Means, GMM and FCM clustering methods (b.)

Feature selection includes methods for dimensionality reduction by generating new features from the initial feature set. For this approach we used principal component analysis (PCA). Two principal components were created by combining several original features, explaining 99.87 percent of variance.

III. Results

For clustering of human activity signals we used three methods:

- K Means
- Gaussian Mixture Model (GMM)
- Fuzzy C Means (FCM)

The reason behind selecting the abovementioned methods lies in their ability to perform with already specified number of clusters, in this case $N = 2$ for both clustering problems. The clustering problems consist of performance analysis of various clustering methods when dealing with four different accelerometer signal data.

The dataset was clustered in two separate occasions depending on accelerometer signal properties. Tables 2 and 3 present the perfomance of cluster methods with signal being labeled depending on the type of human activity represented by given signal and by event type in terms of continuity. Visualization of the cluster results is illustrated in Figure 3. In both cases the number of target clusters N was equal to two.

The results show a disproportion among performance regarding the first cluster labeling criteria and the second, as every clustering method performs better when distinguishing whether a signal belongs to activities of daily living or falls rather than distinguishing the continuity of given activities. As expected, AVM signal analysis performs with better results than sole axis signal analysis. When comparing separate axis datasets, there was no indication to conclude that one axis data that performed significantly better than the others. The expected premise included Y axis dataset to perform with best results since it describes changes in vertical positioning of the sensor, which faces the biggest change in signal behaviour in case of unexpected events such as falling, however that was not the case. When it comes to AVM signal clustering, GMM method performed best for both clustering problems, whilst it is interesting to notice that K Means and FCM perform identically when dealing with AVM data. The recall metric mostly performs with poorer results than precision, which is not ideal in this case since it means that there are more false negative than false positive results. In this case a false negative means that a fall occured, but was not recognized. The main limitation of this study presents the imbalance of clusters (ADL: 680 samples, Fall: 361 sample; continuous activity: 308 samples, single event: 733 samples). In order to overcome limitations to this study, an expansion of the dataset with the collection of new accelerometer data is planned, and eventual sensor fusion of accelerometer data with some other biomarkers (e.g. altimeter data) is expected to improve the research results.

IV. Conclusion

The focus of this research was performing several different clustering analysis on two accelerometer signal datasets depending on their properties. The goal was to get insights on the performance of several clustering algorithms when dealing with different human activities, and whether they can distin-

TABLE II

CLUSTERING RESULTS IN REGARD TO ACTIVITY TYPE

		K means				Gaussian Mixture Model				Fuzzy C-Means			
		Accuracy	Precision	Recall	F_1 score	Accuracy	Precision	Recall	F_1 score	Accuracy	Precision	Recall	F_1 score
X axis	ADL	0.28	0.35	0.13	0.19	0.77	0.81	0.84	0.82	0.74	0.76	0.86	0.81
	Fall		0.25	0.56	0.35		0.67	0.64	0.65		0.66	0.5	0.57
Y axis	ADL	0.33	0.48	0.3	0.37	0.33	0.48	0.34	0.4	0.33	0.48	0.29	0.36
	Fall		0.23	0.39	0.29		0.2	0.32	0.25		0.23	0.41	0.3
Z axis	ADL	0.21	0.2	0.07	0.1	0.78	0.84	0.83	0.83	0.21	0.21	0.08	0.12
	Fall		0.21	0.48	0.3		0.68	0.7	0.69		0.21	0.45	0.28
AVM	ADL	0.89	0.86	0.99	0.92	0.89	0.95	0.89	0.92	0.89	0.86	0.99	0.92
	Fall		0.97	0.7	0.81		0.81	0.91	0.86		0.97	0.7	0.81

TABLE III

CLUSTERING RESULTS IN REGARD TO EVENT CONTINUITY. CE = CONTINUOUS ACTIVITY, SE = SINGLE EVENT

		K means				Gaussian Mixture Model				Fuzzy C-Means			
		Accuracy	Precision	Recall	F_1 score	Accuracy	Precision	Recall	F_1 score	Accuracy	Precision	Recall	F_1 score
X axis	CE	0.6	0.28	0.22	0.25	0.48	0.33	0.76	0.46	0.42	0.31	0.77	0.44
	SE		0.7	0.76	0.73		0.78	0.37	0.5		0.74	0.27	0.4
Y axis	CE	0.5	0.25	0.33	0.29	0.47	0.24	0.38	0.3	0.49	0.33	0.67	0.44
	SE		0.67	0.57	0.62		0.66	0.51	0.58		0.75	0.42	0.54
Z axis	CE	0.56	0.17	0.13	0.15	0.52	0.36	0.78	0.49	0.55	0.18	0.15	0.16
	SE		0.67	0.73	0.7		0.81	0.41	0.54		0.67	0.72	0.69
AVM	CE	0.55	0.39	0.99	0.57	0.68	0.48	0.99	0.64	0.57	0.39	0.98	0.57
	SE		0.98	0.35	0.53		0.99	0.55	0.7		0.99	0.35	0.55

guish activities of daily living from falls, treating it as a binary clustering problem. Another approach included different signal labeling depending on its continuity, exploring the possibility of recognizing and separating a single occurance (e.g. falling or jumping) event from a continuous activity such as running or walking, questioning whether we can gain new insights in the field of human activity recognition and fall detection. Gaussian Mixture Model (GMM) proved to perform best regarding both the first (89% accuracy, 92% F_1 score for ADL and 86% F_1 score for falls) and the second clustering problem (68% accuracy, 64% F_1 score for continuous activities and 70% F_1 score for single events) . Given the fact that the dataset used in this research was somewhat scarce (1041 total signals, 680 ADL and 361 fall signals), the achieved results indicate promise for further research.

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