DU-MD: An Open-Source Human Action Dataset for Ubiquitous Wearable Sensors

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Abstract—Human Action Recognition (HAR) in healthcare amongst senior citizens focuses on remote surveillance, healthcare monitoring and fall detection. The wearable approach, in particular, wrist-mounted sensors for HAR is most favorable when qualitative characteristics, parameter complexities and market projections are considered. Machine learning models for Activities of Daily Living (ADL) / fall detection require large, hardware-independent and comprehensive ADL datasets exhibiting statistical variance and closeness to real life cases. However, there is a lack of public motion traces filling in all necessary obligations. In this context, the University of Dhaka (DU) Mobility Dataset (MD) was built using 25 subjects (out of 50) have provided 10 classes of ADL, with 2500 (out of a final 5000) training sets using a single wrist-mounted wearable sensor. Some existing public databases have been compared extensively and assembly of the wearable sensor using the recently developed UTokyo Trillion Node Engine Project is illustrated. Statistical tests have been carried out to ensure diversity whilst accuracy of the dataset using existing statistical mechanisms have been acknowledged. Promising diversity and accuracy make this dataset suitable for use in wrist-mounted healthcare monitoring systems.

Keywords—Human Action Recognition (HAR), Activities of Daily Living (ADL), Wearable, Accelerometer, ANOVA

I. INTRODUCTION

Human Action Recognition (HAR) is defined as the process of finding the correlation of an input with analogous data from a data bank, with the input being a succession of action primitives, which are granular microscopic events with pragmatic significance [1]. Eclectic and noteworthy applications of HAR include surveillance, haptics, human-machine interaction and healthcare monitoring [2]. Approaches for HAR in healthcare, in particular, Activities of Daily Living (ADL) and fall detection in senior citizens consist of the wearable approach, the vision-based approach and ambient device based approach [3]. Qualitative infalliability in relative inexpensiveness, specificity, sensitivity, portability, real-time processing and lucid setup, with a positive trend in acceptability amongst senior citizens, favor the wearable approach for non-controlled environments [3][4][5][6]. Principles and techniques of HAR using wearables can be classified into accelerometry (most widely used), gyrometry, magnetometry and sensor fusion [3][5]. Both analytical methods (such as change in orientation and thresholding) and machine learning models have been extensively applied in several published manuscripts for HAR using accelerometry [3][6][7].

Application of machine learning techniques require the presence of comprehensive ADL datasets involving the exercise of some classification techniques, clustering algorithms, decision trees and semi-supervised artificial and convolutional neural networks in order to correctly distinguish between a class of actions. In particular, machine learning algorithms classifying a large number of classes require a large training set [8] encompassing copious natural complexities, statistical unbiasedness, varied scenarios and parameter variance. According to Mi Zhang et. al [9], a HAR dataset should exhibit the following characteristics:

- The subjects must show statistical variance in physiological parameters such as age, gender, weight and height.
- The ADL should contain some rudimentary actions such that the bandwidth of its applicability increases.
- The data logger should be able to minimize noise and sample the command input accurately.
- Position of the data logger should follow the near-future trends in wearables amongst the target subjects.

The University of Dhaka Mobility Dataset (DU-MD) attempts to embrace the aforementioned characteristics and provide a dataset suitable for exercise of machine learning algorithms for fall/ADL detection in existing wrist mounted wearables (such as fitness bands) containing accelerometers and targeted towards senior citizens. At the time of writing (April 2018), 25 subjects (out of 50) have provided 10 classes of ADL, with 10 training sets per ADL, amounting to 2500 (out of 5000) unique training sets. The raw (unprocessed) dataset is currently available at: eee.du.ac.bd/DU-MD

II. COMPARISON WITH EXISTING DATASETS

Several HAR datasets for the wearable approach exist, each with its own unique features, pros and cons. Some widely used datasets [5] include:
Several important insights from these 6 standard datasets are as follows:

- **Only UMAFall has fall waveforms. Other datasets are hence, not usable for fall detection.**
- **Data loggers used in HAR, HAD and HAPT datasets were positioned on the waist and hip. However, not all locations are suitable for wearables when factors such as subject comfort and feasibility are incorporated [5]. For example, the HAR dataset used a smartphone attached to a belt around the waist, which is neither comfortable nor feasible in a pragmatic scenario. In fact, activity trackers and fitness bands designed to be worn on the wrist are now being more integrated into the lives of senior citizens with a positive trend in acceptability [16]. The most plausible explanation behind the lack of interest in wrist-mounted HAR is the slightly degraded performance of algorithms compared to other locations [17], however, considering consumer demand, the major sales of wearables are sourced from wrist-mounted types as of 2017 [18]. As a result, the goal of HAR datasets should be to support building software for existing wrist mounted smartbands rather than introducing new hardware.**
- **With the exception of the HASC dataset, most datasets used a few subjects in a controlled environment. However, machine learning for HAR requires a large dataset for training.**
- **The HASC and HAR datasets consider only a few basic ADL (few classes).**
- **The age of subjects are usually 19-48 years old. As a result, the dataset is not perfectly calibrated if the target audience concentrates towards senior citizens.**

Several other datasets focusing on both fall and ADL detection are mentioned in literature [15]. Only the TST Fall Detection Dataset and SINTEF ICT Dataset used wrist mounted sensors, whilst tFall and UniMiB Shar dataset consider sufficient training sets (>5000) to be able to train most machine learning algorithms, especially deep neural networks [19]. On the other hand, only the Cogent Labs dataset, MobiAct Dataset and SisFall Dataset consider a large number of subjects (>30) to ensure statistical variance in physiological parameters discussed earlier. The UMAFall dataset used a thick mattress for falls, which may result in different acceleration characteristics as it is only an approximation of real life falls [20].

The DU Mobility Dataset has the following coveted features, making it suitable for HAR geared towards senior citizens:

- **Considers 7 types of ADL and 3 types of falls common in senior citizens.**
- **Portable with existing wrist-mounted wearables (hardware independent).**
- **Large number of subjects (50) for ensuring variance in physiological parameters.**
- **Large number of training sets (~5000).**
- **Falls simulated directly on the floor with limited protective equipment to simulate real life cases.**
- **High bandwidth of data logger for detailed sampling (5.3 kHz).**
- **Open-source, flexible, tiny and customizable IoT platform utilized for data logging.**

### III. MATERIALS AND METHODS

#### A. System Architecture

The open-source and configurable Internet of Things (IoT) platform developed at the Institute of Industrial Science, University of Tokyo, also known as the Trillion Node Engine Project was used to create the data logger [21]. The modules utilized were the 8 Bit Microcontroller Leaf, 8 bit USB UART Adapter Leaf, Li-Ion Battery Leaf, Micro-SD Leaf and Sensor Leaf (only LIS2DH was used). For motion activity recognition and fall detection, the LIS2DH triaxial MEMS accelerometer
has been used. Several characteristics [22] make this sensor suitable for this purpose:

- **Large Dynamic Range:** ± 2g, ± 4g, ± 8g, ± 16g.
- **Low Operating Voltage:** 1.71 - 3.6 V (2.5V typical)
- **Low Current Consumption:** Minimum: 0.5 µA, Maximum: 11 µA.
- **Modes:** High Resolution, Low Power, Normal Mode.
- **High Bandwidth:** 5.3 kHz.

Figure 1 shows the leaf assembly of the data logger.

The electronic components reside within an acrylic chassis fabricated using a laser cutter. The chassis, in turn, is glued firmly atop an old wrist watch, providing a robust wearable data logger eliminating unwanted vibrations. The accelerometer transmits data via I2C bus to the microcontroller platform. The microcontroller reads data at a rate of 30 samples/second. The data is saved in a text file in the SD card via the SD card module. The entire platform is powered by a rechargeable Li-Ion battery. The programmer, which is unused during the data logging process, can be used to program the microcontroller using a computer when required. The data logging algorithm, which records the acceleration in x, y and z axis, is shown in Figure 2 (zoom in for clearer view).

Figure 3 shows the simulated model of the accelerometer and Figure 4 shows the typical response of the accelerometer for standard input ($T_s >> 1/BW$).

**B. Description of the Testbed: Assumptions and Scenarios**

Each subject was provided with only basic protective equipment (to preserve realism) comprising of cycling gloves (to prevent palm abrasions), knee pads (to protect against scrapes), elbow pads (to prevent scrapes) and arm pads (to prevent arm abrasions). The data logger was worn on the dominant wrist. Figure 5 shows the typical getup of a test subject.
The scenarios in the testbed are as follows:

- Falls were mimicked on both tiled (inside FAB LAB DU) and stoned floors (inside classrooms). No mattresses were used.
- For ADL related to climbing staircases, all subjects climbed a staircase containing 10 steps.
- All ADL excluding falls and staircase climbing/down were executed for approximately 10 seconds.

The assumption pertaining to the testbed are as follows:

- The acceleration waveforms created upon falling is similar to expected real life waveforms.
- All traces (excluding falls and staircase climbing/down) have an analogous number of samples (~300). All staircase related ADL also would have a similar number of samples amongst them.
- The subject was not distracted in any way or did not encounter an obstruction in the path such that the data logging would be hampered.
- The wearable did not come loose while taking readings.
- Ground truth annotation [9]: Either of the authors were present during the activities and ensured validity of the procedure in which the readings were being taken.

C. Subjects and Activities

10 classes of actions were recorded, illustrated in Table I.

<table>
<thead>
<tr>
<th>ADL</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Walking</td>
<td>Each subject walked forward freely in a straight line, and walked back through the same route.</td>
</tr>
<tr>
<td>2 Sitting</td>
<td>Each subject sat freely on a classroom desk for 10 seconds.</td>
</tr>
<tr>
<td>3 Lying</td>
<td>Each subject lay on a table in various sleeping positions.</td>
</tr>
<tr>
<td>4 Jogging</td>
<td>Each subject jogged forward in a straight line, turned and jogged back through the same route.</td>
</tr>
<tr>
<td>5 Staircase Climbing</td>
<td>Each subject climbed 10 steps.</td>
</tr>
<tr>
<td>6 Staircase Down</td>
<td>Each subject came down 10 steps.</td>
</tr>
<tr>
<td>7 Standing</td>
<td>Each subject stood freely for 10 seconds</td>
</tr>
<tr>
<td>8 Falling (Unconscious)</td>
<td>The subject acted as if he/she is feeling dizzy by clinching the head and then falling freely on the ground.</td>
</tr>
<tr>
<td>9 Falling (Heart Attack)</td>
<td>The subject acted as if he/she is feeling pain in the chest by clinching the left side of the chest and then falling freely on the ground.</td>
</tr>
<tr>
<td>10 Falling (Walk &amp; Fall)</td>
<td>The subject walked normally for a certain distance and then suddenly fell freely.</td>
</tr>
</tbody>
</table>

At the time of writing, 25 subjects (17M, 8F) had provided readings. The age, weight and height of the subjects were noted and the statistics are provided in Table II.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Age (yrs)</th>
<th>Weight (kg)</th>
<th>Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>[16-22]</td>
<td>[40-101]</td>
<td>[1.47-1.82]</td>
</tr>
<tr>
<td>Mean</td>
<td>19.12</td>
<td>59.9</td>
<td>1.66 (F - 1.58; M - 1.69)</td>
</tr>
<tr>
<td>Median</td>
<td>19</td>
<td>54</td>
<td>1.65</td>
</tr>
<tr>
<td>SD</td>
<td>±1.24</td>
<td>±10.03</td>
<td>±0.086</td>
</tr>
</tbody>
</table>

From Table II, the average mass of subjects obtained was 59.9 kg, which is very close to the average adult mass of 62 kg [23]. The average heights of an adult male and female are 1.7 and 1.6 m, respectively, which are reflected in the obtained average heights as well.

D. Description of the Files

The opening web page consists of several folders corresponding to test subjects in the following format: n_name, e.g. 1_SrimanBidhanBaray. Each subfolder inside a folder corresponds to an ADL for a particular test subject. There are 10 subfolders inside each folder. Each subfolder consists of around 10 text files in the following format: xxn.TXT, e.g. xx01.TXT. Data from each textfile can be readily imported into programming IDEs such as MATLAB or Microsoft Azure via standard functions.

IV. RESULTS

A. Statistical Diversity Tests

The box plots for age, weight and height are shown in Figure 6.

![Figure 6. Box plots for age, weight and height.](image-url)
From Figure 6, the age is slightly negatively skewed, the weight is strongly positively skewed and the height is slightly positively skewed. All three parameters are platykurtic, hence a sub-Gaussian distribution should be suitable to model the parameters [24] and all three parameters (especially weight and height) should pass normality tests. Table III summarizes the results from the Kolmogorov Smirnov test [25].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DF</th>
<th>Statistic</th>
<th>P &gt; D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (yrs)</td>
<td>25</td>
<td>0.34132</td>
<td>0.0042</td>
</tr>
<tr>
<td>Weight (kg)</td>
<td>25</td>
<td>0.18228</td>
<td>0.33696</td>
</tr>
<tr>
<td>Height (m)</td>
<td>25</td>
<td>0.18228</td>
<td>0.33696</td>
</tr>
</tbody>
</table>

- Age: At the 0.05 level, the data was not significantly drawn from a normally distributed population.
- Weight: At the 0.05 level, the data was significantly drawn from a normally distributed population.
- Height: At the 0.05 level, the data was significantly drawn from a normally distributed population.

The apparent discrepancy for age in the K-S Test may arise from the fact that most test subjects were freshmen, with all ages cluttering near the mean, apparent in the box plot for age as well. If we assume that the confidence interval for age is 0.90, then statistically, the source of the dataset may be considered sufficiently diverse and unbiased. The histograms and normalized distributions for the three parameters are shown in Figure 7.

![Figure 7](image)

Figure 7. Histograms with normalized distributions for age, weight and height.

It is expected that these three parameters will be more uniformly distributed once all 50 test subjects are taken into consideration altogether.

B. Typical Visualizations

Figure 8 shows example activity data in three axis \((A_x, A_y, A_z)\) and their vector sum \(\sqrt{A_x^2 + A_y^2 + A_z^2}\). The text in red indicates the expected class in which the sensor classifies a given activity window, while the text in black indicates actual action.

![Figure 8](image)

Figure 8. Example activity classification for a given waveform. The vector sum is a common analytical feature of wearable acceleration data widely used in thresholding algorithms [26].

Wavelet transforms are useful for denoising and pattern recognition [27]. Figure 9 shows the application of wavelet transform and spectral analysis on random “walking” ADL.

![Figure 9](image)

Figure 9. (Left) Application of wavelet transform to a particular feature for denoising, simplification and making the feature ready for pattern recognition. (Right) The normalized power spectral density (PSD) and spectrogram of the vector sum to detect patterns in PSD.

Symlets (sym2, level 5) have been used for denoising and simplification. The noise structure was unscaled white noise whilst the thresholding method was soft fixed form threshold. Decomposition levels were varied until the suitable pattern shown in Figure 9 (left) was found. Patterns may also be found...
from PSD for different ADL signals [28]. The recommended approach is to clean the raw data and take samples of ADL of equal length, denoise and establish suitable patterns using wavelet transform or PSD and then train the machine.

C. Accuracy Tests

Kruskal-Wallis one way ANOVA [25] was performed on 10 walking ADL by a single subject containing 101 samples each. Table IV summarizes the results of the test.

| TABLE IV. Results from K-W One Way ANOVA |
|---|---|---|
| C | 100 | 100 | 0.48119 |

At the 0.05 level, the populations are not significantly different, justifying accuracies of similar ADLs.

V. CONCLUSION

This paper serves to introduce the open-source DU Mobility Dataset, which currently consists of 10 ADL/falls from 25/50 subjects, creating approximately 2500/5000 training sets. The dataset is suitable for wrist mounted ubiquitous sensors, driven by accelerometer and deep neural networks. By attempting to solve some of the shortcomings of other datasets, DU-MD makes itself much coveted for HAR. In future, apart from completing the dataset, existing machine learning models will be applied in order to deduce the relative robustness of the dataset itself.

ACKNOWLEDGEMENT


REFERENCES