How Long Are Various Types of Daily Activities? Statistical Analysis of a Multimodal Wearable Sensor-based Human Activity Dataset

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Abstract: Human activity research in the field of informatics, such as activity segmentation, modeling, and recognition, is moving in an increasingly interpretable direction with the introduction of sports and kinematics knowledge. Many related research topics face a question: How long is the typical duration of the activities needed to be modeled? Several public human activity datasets do not strictly limit single motions' repetition times, such as gait cycle numbers, in recording sessions, so they are not statistically significant concerning activity duration. Standing on the rigorous acquisition protocol design and well-segmented data corpus of the recently released multimodal wearable sensor-based human activity dataset CSL-SHARE, this paper analyzes the duration statistics and distribution of 22 basic single motions of daily activities and sports, hoping to provide research references for human activity studies. We discovered that (1) the duration of each studied human daily activity or simple sports activity reflects interpersonal similarities and naturally obeys a normal distribution; (2) one single motion (such as jumping and sitting down) or one cycle in the activities of cyclical motions (such as one gait cycle in walking) has an average duration in the interval from about 1 second to 2 seconds.

1 INTRODUCTION

In today's highly automated society, human activities are being studied more and more widely in the field of Artificial Intelligence (AI) to facilitate human life, such as in medical care (Ejupi et al., 2016), interactive interfaces (Ancans et al., 2017), and multimedia entertainment (Jung and Cha, 2010) (Zok, 2014). Generally speaking, human activity can refer to all behaviors related to human beings, such as brain activity, which do not need to produce any movement. However, when we use the concept of "human activity" in the research category of Machine Learning (ML), we generally mean the connotation of kinematics, for which the concept "motion" matches more closely. More specifically, a human activity refers to the movement(s) of one or several parts of the person's body, either atomic or composed of many primitive actions performed in some sequential order (Beddiar et al., 2020). Therefore, human activity has a broad denotation: It can refer to a single human motion in a narrow sense, such as jumping, walking, and most gestures, or a human motion sequence of concurrent, coupled, and sequential motions in a broad sense, like cutting a cake, as described in (Gehrig, 2015). Moreover, in most public human activity datasets, some postures which do not produce substantial movement, such as standing and sitting, are also categorized as the scope of (static) human activity, since these activities can also be recognized separately, given suitable equipment.

Many ML research topics related to human activities, such as segmentation, modeling, and recognition, face a question: How long is the duration of the activity that needs to be modeled? For offline activity modeling, the knowledge of activity duration can help estimate the model parameters at the outset, such as layer numbers in the Neural Network (NN) or state numbers in the Hidden Markov Model (HMM). For online research like real-time or streaming-based Human Activity Recognition (HAR), the duration of the activities to be recognized will help seek a better trade-off between window length, window overlap, and performance delay (Liu and Schultz, 2019).

In sports science, activity duration is usually a common measurement task, but there are few research works where these measurement results are adequately used in ML research. In kinematics, gait

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analysis provides a good model hypothesis (Mezghani et al., 2013) (Whittle, 1996) (Whittle, 2014) (Arous et al., 2018), but there are few related statistical references based on signalized kinematic data, except that (Lanshammar, 1987) estimated gait cycle duration and stride length from one-marker kinematic data. Therefore, it is essential to conduct a statistical activity duration analysis from the perspective of human activity data mining.

Some human daily activities, such as sitting and vacuuming, can last for half an hour or only a few seconds. Hence, among all definitions and divisions of human activities, two categories, in which the activity duration varies from person to person, from task to task, and from dataset to dataset, are not statistically informative in terms of duration:

- Postures, which can maintain a steady body state for any duration, such as standing, sitting, lying, squatting, among others;
- Activities of sequential motions, such as cooking, vacuuming, watching TV, among others.

This paper focuses on analyzing the duration statistics and distribution of single motions. No matter the motion contains only one movement, such as one-leg jumping, two-leg jumping, standing up, sitting down, and turning left/right, or several continuous looping cycles, such as walking, running, going upstairs/downstairs, and lateral shuffling, its duration has the statistical value of interpersonal similarity, which not only provides a powerful reference for modeling but also may facilitate processing more complex motion sequences.

2 DATASET

Except for some human activity datasets that involve relatively small numbers of defined activities, such as *RealWorld* (Sztyler and Stuckenschmidt, 2016), *ENABL3S* (Hu et al., 2018), and *Gait Analysis Data Base* (Loose et al., 2020), or only activities of particular body parts, such as *mmGest* for gesture (Georgi et al., 2015), *CSL hdemg* for finger (Amma et al., 2015), and *Upper-body movements* (Santos et al., 2020), most of the existing public human activity datasets, such as *OPPORTUNITY* (Roggen et al., 2010), *PAMAP2*, (Reiss and Stricker, 2012), *Daily Log* (Sztyler et al., 2016), and *FORTH-TRACE* (Karagiannaki et al., 2016), cannot be directly applied to the statistical analysis of activity duration because of the following two reasons:

- Unrestricted acquisition protocol designs. For example, the activity "walking" itself can last for any duration, but each gait cycle of a healthy adult can be statistically analyzed; however, there are few datasets stipulating each "walking" segment with a fixed number of gait cycles strictly;
- Distinct activity segmentation methods. For example, the *UniMiB SHAR* dataset (Micucci et al., 2017) implements a simple way of finding the magnitude peak of the acceleration signals to segment 17 classes of Activities of Daily Living (ADLs) and falls. Whether it is walking, jumping, or falling forward, each activity segment is precisely 3 seconds. This kind of segmentation is easy and efficient with almost no manual labor or machine learning study but can hardly be applied for accurate human activity duration analysis.

The data support we use is a multimodal wearable sensor-based human activity dataset called *CSL-SHARE* (Liu et al., 2021a), whose quality and applicability have been extensively verified in many research fields of human activities, such as HAR research pipeline (Liu et al., 2022), feature extraction (Barandas et al., 2020), feature space reduction (Hartmann et al., 2021) (Hartmann et al., 2022), automatic segmentation, human activity modeling and recognition (Liu et al., 2021b), among others. A knee bandage was used as a wearable sensor carrier, making the dataset distinctive and more kinematically significant. The 19-channel dataset was recorded from 9 biomechanical and bioelectrical sensors, including 2 triaxial accelerometers, 2 triaxial gyroscopes, 4 EMG sensors, 1 biaxial electrogoniometer, and 1 airborne microphone with sampling rates up to 1,000 Hz. By applying the in-house implemented software *Activity Signal Kit* (ASK) (Liu and Schultz, 2018) for data acquisition, segmentation, and annotation, the *CSL-SHARE* dataset covers 22 types of ADLs and sports from 20 subjects, 5 female and 15 male, aged between 23 and 43 (30.5 ± 5.8), in a total time of 11.52 hours, of which 6.05 hours are segmented and annotated.

Unlike many human activity datasets listed above, the *CSL-SHARE* dataset adopts strictly defined acquisition protocols and a semi-automatic segmentation mechanism called "protocol-for-pushbutton", enabling efficient and accurate statistical analysis of single motions. In addition to strictly stipulating "three gait cycles" and "left-foot-first" for gait-based activities such as walking, running, going upstairs/downstairs, and left/right lateral shuffling, it is worth mentioning that the *CSL-SHARE* dataset also distinguishes some activities with left-foot-first or right-foot-first, providing materials for similarity analysis of activity duration.

Table 1: Statistics of the single motion segment duration in the CSL-SHARE dataset. The minimum, maximum, mean, and standard deviation (std.) values are in seconds.

Activity	**Minimum**	**Maximum**	**Mean±std.**	**Number of segments**
jump-one-leg	0.830	2.949	1.69 ± 0.33	379
jump-two-leg	0.869	3.389	1.95 ± 0.39	380
walk (one gait cycle)	1.046	1.863	1.42 ± 0.15	400
walk-curve-left 90° (one gait cycle)	0.966	2.150	1.45 ± 0.19	398
walk-curve-right 90° (one gait cycle)	1.076	2.063	1.48 ± 0.17	393
walk-upstairs (one gait cycle)	1.263	2.243	1.59 ± 0.15	365
walk-downstairs (one gait cycle)	1.023	1.973	1.44 ± 0.17	364
spin-left-left-first	0.959	3.069	1.67 ± 0.30	380
spin-left-right-first	0.969	2.609	1.83 ± 0.29	420
spin-right-left-first	0.800	2.619	1.86 ± 0.24	401
spin-right-right-first	1.169	2.719	1.71 ± 0.22	400
run (one gait cycle)	0.773	1.373	1.05 ± 0.11	400
shuffle-left (one gait cycle)	0.580	1.290	0.96 ± 0.10	380
shuffle-right (one gait cycle)	0.696	1.386	0.97 ± 0.11	374
V-cut-left-left-first	0.809	3.039	1.81 ± 0.33	399
V-cut-left-right-first	1.019	2.709	1.88 ± 0.29	378
V-cut-right-left-first	0.840	2.759	1.80 ± 0.34	400
V-cut-right-right-first	1.209	2.649	1.84 ± 0.28	378
sit-to-stand	1.049	2.719	1.81 ± 0.32	389
stand-to-sit	1.129	3.729	1.92 ± 0.35	389
sit	0.819	8.019	1.66 ± 0.58	389
stand	0.809	6.959	1.64 ± 0.51	405

3 ACTIVITY DURATION ANALYSIS

Table 1 gives the number of activity segments and the minimal/maximal/mean duration of the 22 activities in the *CSL-SHARE* dataset. It should be noted that, unlike the statistics of the table given in (Liu et al., 2021a), for the eight activities involving three complete gait cycles, we only list the statistics of one gait cycle to create referenceability for other research.

Judging from each activity segment's number of occurrences, we can find that this dataset is well-balanced for each involved activity, reflecting strict protocol design and execution. Each activity was planned to be performed 20 times by each participant according to the protocols. The activity occurrence discrepancy in Table 1 is mainly due to eliminating the misoperation during users' execution of the semi-automatic segmentation mechanism.

Since the pushbutton for segmentation and annotation may be pressed/released earlier or later during the acquisition process, millisecond-level operation-related slight duration deviations make the minimum and maximum values' general statistical reference of minor significance; however, they are still meaningful when using the *CSL-SHARE* dataset for modeling research. Due to the big data effect of multiple participants and multiple activity execution times, the impact of individual operational discrepancy is compensated to a high degree on the average/standard deviation values in Table 1. Furthermore, it is noteworthy that the video-based manual post verification after each data collection process corrected obvious duration outliers.

From Table 1 we can deduce a statistical hypothesis: One single motion (such as jumping and sitting down) or one cycle in the cyclical single motions (such as one gait cycle in walking) has an average duration in the interval from about 1 second to 2 seconds, which can help determine a priori some parameters for data segmentation, feature extraction, activity modeling, model training, and recognition (Hartmann et al., 2020) (Liu, 2021). It must be stressed that the dataset was recorded from only healthy young to middle-aged adults. In fact, except for unique application scenarios, ML research often starts at this age group. Moreover, for biomedical engineering, data of healthy individuals is usually the first material for establishing an applicable model, which also creates reliable references for the study of pathological situations.

The following subsections will analyze the duration statistics of each activity group and their distribution.

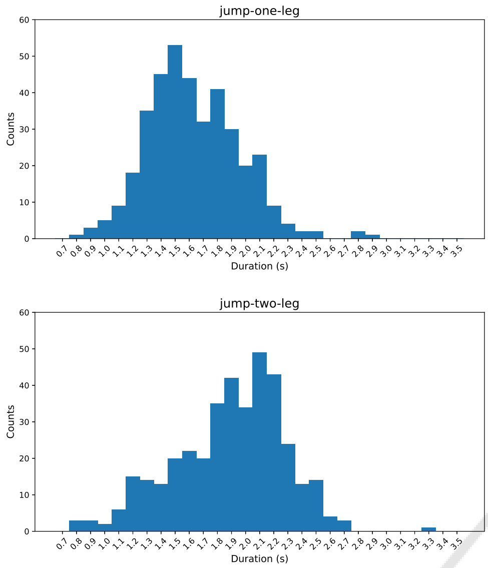

Figure 1: Duration histograms of the human activities **jump-one-leg** and **jump-two-leg** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 100-millisecond intervals.

3.1 Jumping Activities

The acquisition protocols for single-leg and two-leg jumping activities in the *CSL-SHARE* dataset are described as "squat, then jump upwards using the bandaged right leg/both legs, land in" (Liu et al., 2021a).

Table 1 and Figure 1 demonstrate that the average duration of the two jumping activities is within the interval of 1.6 – 2.0 seconds, and the duration of a single-leg jump is about 86% shorter than that of a two-leg jump. It is more challenging to keep balance during the single-leg squat, so subjects generally shortened the time and amplitude of the single-leg squat and tended to jump as soon as possible. Therefore, the relatively reduced muscular power in the single-leg jump also shortens the body's stay-in-the-air (fly) time, compared to a well-prepared two-leg jump. This phenomenon is also witnessed by their half-second maximum duration difference, while the minimum values are close. Participants tended to be more prepared for the squat in two-leg jump.

Jumping activities are certainly not only restricted to the direction of upwards — it can be forwards-upwards, or even leftwards/rightwards. Physically speaking, regardless of what kind of jump happens, as long as it happens daily and generally without a particular purpose like a header shot, there should be no apparent difference in duration statistics.

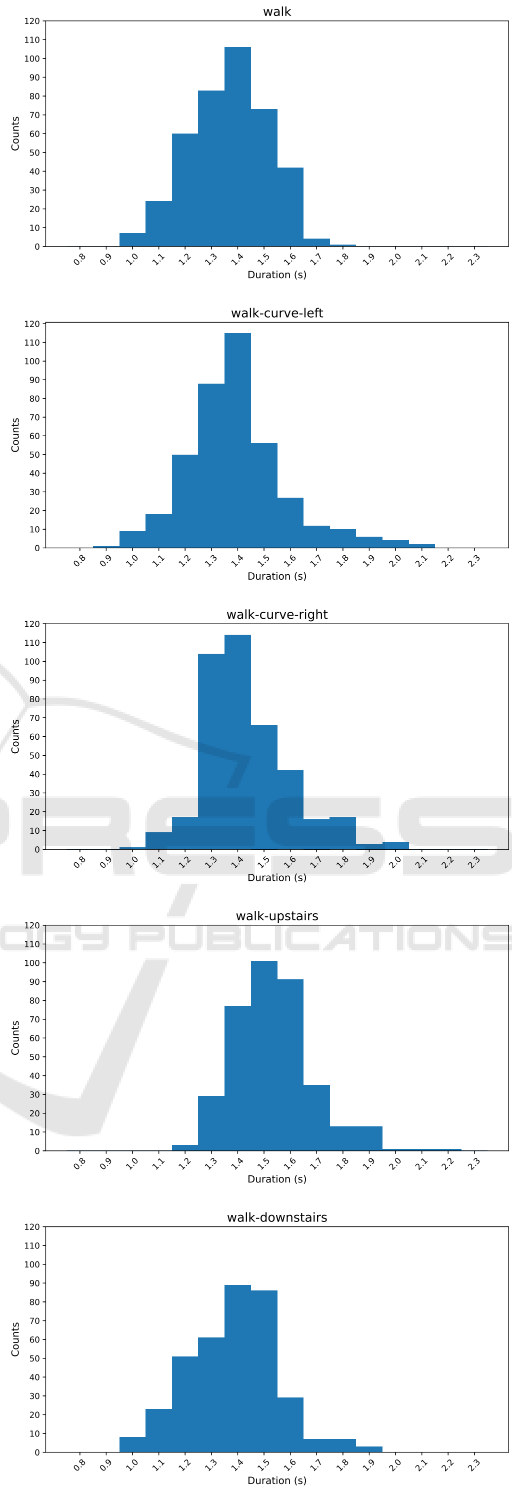

Figure 2: Duration histograms of one gait cycle in the cyclical motions **walk**, **walk-curve-left**, **walk-curve-right**, **walk-upstairs**, and **walk-downstairs** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 100-millisecond intervals.

3.2 Activities of Gait-based Cyclical Motions at Waling Speed

The acquisition protocols for the five gait-based cyclical motions in the *CSL-SHARE* dataset are described as follows (Liu et al., 2021a):

- Walk: walk forward with three gait cycles, left foot starts, i.e., left-right-left-right-left-right;
- Walk-curve-left/right: turn left/right 90° with three gait cycles at walking speed, left foot starts;
- Walk-upstairs/downstairs: go up/down six stairs with three gait cycles, left foot starts.

As mentioned above, in order to establish a universal reference, we only describe one-gait-cycle statistics in Table 1 and Figure 2.

Regardless of the direction, the duration of a gait cycle at daily walking speed is about 1.4 to 1.6 seconds. Obviously, when turning left/right or going upstairs/downstairs during walking, the average gait cycle duration is slightly longer than the normal straightforward walking, among which walking upstairs leads a duration of about 100 – 200 milliseconds longer on average. It can also be observed that although walking downstairs saves 10% of the time than upstairs, it is not faster than walking straightforward. In real life, walking downstairs is considered a fast movement than other types of walking, but in the laboratory data acquisition sessions, participants tended to go downstairs at a relatively normal speed in a relaxed environment. Another thing to remind is that the height of the stairs will also affect the activity duration. The stairs used in the *CSL-SHARE* dataset are the regular building stairs of standard height.

3.3 Single-gait Activities at Walking Speed

The "spin-left" and "spin-right" activities in the *CSL-SHARE* dataset can be described as the "Left face!" or "Right face!" action in the army (but in daily situations, not so stressful as in military training). The acquisition protocols are designed as "turn left/right 90° in one step, left/right foot starts" (Liu et al., 2021a). "Spin-left" is divided into "spin-left-left-first" and "spin-left-right-first," denoting which foot should be moved first. Similarly, "spin-right" is also divided into two activities in regard to the first-moved foot. The reason for the subdivision is that these activities only involve one gait cycle, and the data acquisition only uses the sensors placed on the right-leg-worn bandage. Therefore, the "left-foot-first" and "right-foot- first" of these activities will lead to very different signal patterns. On the contrary, activities involving multiple gait cycles (see Sections 3.2 and 3.4) are not subdivided according to the first-moving foot.

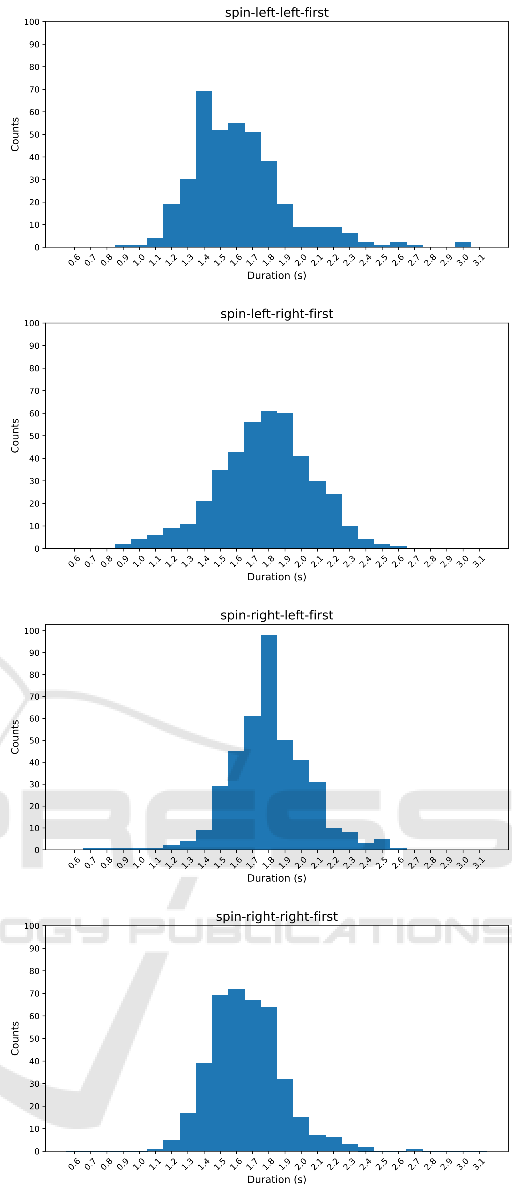

Figure 3: Duration histograms of the single-gait human activities **spin-left-left-first**, **spin-left-right-first**, **spin-right-left-first**, and **spin-right-right-first** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 100-millisecond intervals.

As Table 1 and Figure 3 exhibit, the average duration of 90° single-gait turns is larger than a single gait cycle in walking activities due to the large turning angles. The average duration is about 1.6 – 1.9 seconds. It takes 9% more time to start with the right foot in a left turn or start with the left foot in a right turn than to start with the same side foot in the turning direction.

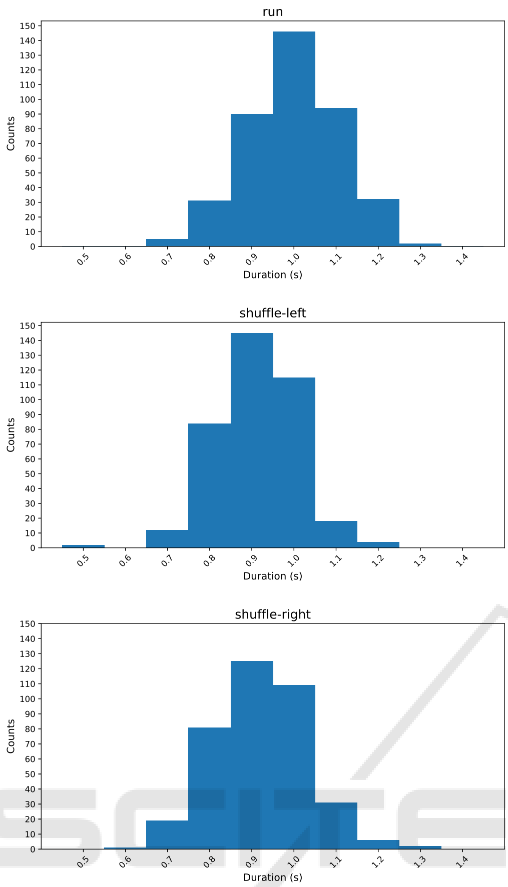

Figure 4: Duration histograms of one gait cycle in the cyclical motions **run**, **shuffle-left**, and **shuffle-right** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 100-millisecond intervals.

3.4 Activities of Gait-based Cyclical Motions at Fast Speed

The acquisition protocol of "run" is basically the same as that of "walk," except the fast speed, while the protocols of "shuffle-left/right" demand the subject to "move leftward/rightward with three lateral gaits cycles, left/right foot starts, the other foot follows" (Liu et al., 2021a).

One gait cycle of the sports-related lateral shuffling, as Table 1 and Figure 4 display, is the fastest motion in the entire *CSL-SHARE* dataset, followed by running. Their duration is around 1 second. Limited to laboratory conditions, running was actually performed at jogging speed instead of reaching full speed in sports.

Roughly speaking, the duration of a single gait at a fast-paced speed is about 30% shorter than at a walking speed. It can be highlighted that these three shortest motions' statistics present the least standard deviations from subject to subject in the whole dataset.

3.5 Single-gait Activities at Fast Speed

"V-cut" in the *CSL-SHARE* dataset refers to the single-gait motion of direction changing during running.

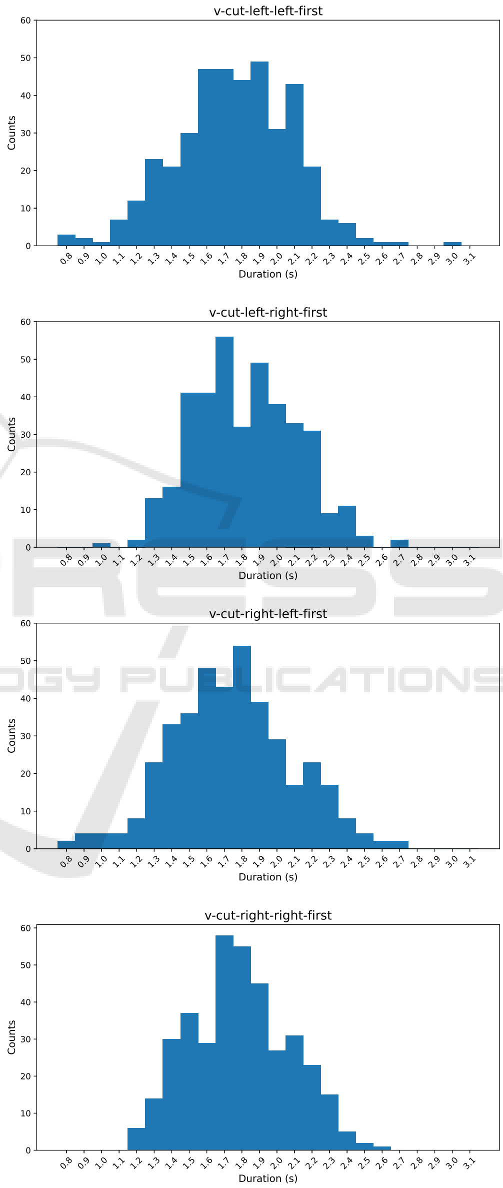

Figure 5: Duration histograms of the single-gait human activities **v-cut-left-left-first**, **v-cut-left-right-first**, **v-cut-right-left-first**, and **v-cut-right-right-first** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 100-millisecond intervals.

The acquisition protocols of "V-cut" are stipulated as follows: "turn 30° left/right forward in one step at jogging speed, left/right foot starts" (Liu et al., 2021a). Similar to the "spin" activities, both "V-cut-left" and "V-cut-right" are divided into two activities regarding the first-moved foot, separately, due to the same reason as explained in Section 3.3.

The average duration of all four "V-cut" activities falls within 1.8 seconds to 1.9 seconds, as Table 1 and Figure 5 indicate. Compared to the fact that there is a significant duration difference of which foot is moved first in the "spin" activities, for both "V-cut-left" and "V-cut-right", which foot is moved first affect only slightly the activity duration, for which two reasons can explain: Firstly, the "V-cut" activities themselves require a large step with intense muscular preparation, where which foot to step first has no significant influence; Secondly, it is stated in the protocol that by "V-cut", subjects only need to rotate 30°, which is one-third of the 90° in spin activities (this is also in line with common sense — it's easy to turn 90° while walking, but directional changing at fast speed requires a larger motion radius).

Interestingly, whether turning 30 degrees to the left or the right, starting with the right foot always causes a little longer duration in average.

3.6 Activities of Transition between Standing and Sitting

Figure 6 illustrates that the "stand-to-sit" activity, i.e., sitting down, has a similar duration distribution to "sit-to-stand", i.e., standing up. However, according to Table 1 and Figure 6, it is noticeable that averagely, sitting down is about 100 milliseconds longer than standing up and has more outlier samples with long duration, which is consistent with real-life situations: The knee flexion is more difficult to act than the knee extension, and a certain sense of organ self-protection often accompanies knee bent.

3.7 Postures: Standing and Sitting Activities

Like many public human activity datasets (see Section 2), *CSL-SHARE* also includes standing and sitting activities, which should be classified as postures. Nevertheless, as mentioned in Section 1, these two activities are considered no significant interindividual statistical reference, for which some clues can be glimpsed through the long duration outliers in Figure 7. Due to the outlier maximum duration values, these two histograms use a 200-millisecond interval, different from

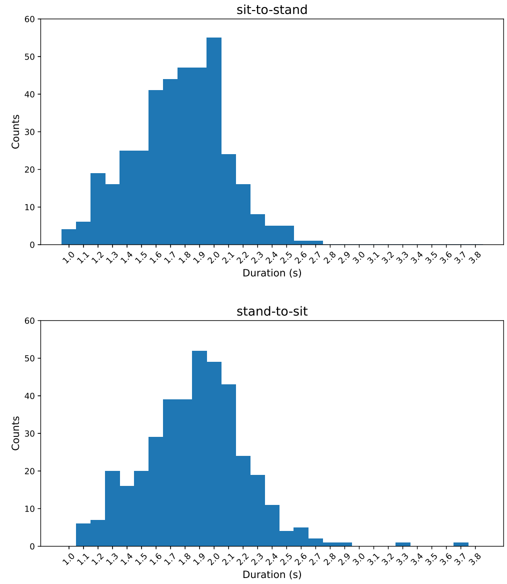

Figure 6: Duration histograms of the human activities **sit-to-stand** and **stand-to-sit** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 100-millisecond intervals.

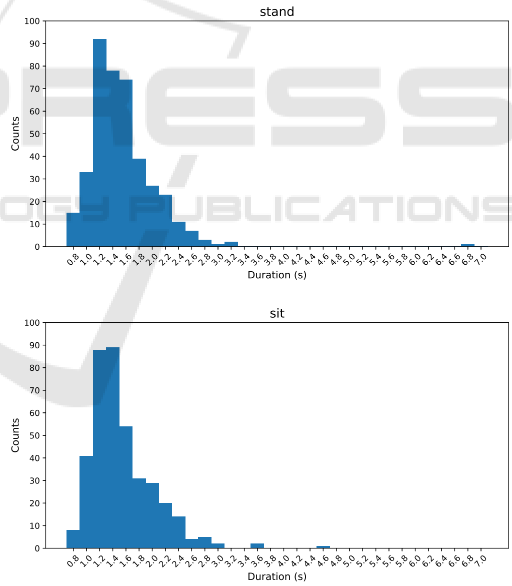

Figure 7: Duration histograms of the segmented postures **stand** and **sit** in the *CSL-SHARE* dataset. The area under the curve equals the total number of segment occurrences within 200-millisecond intervals.

the 100-millisecond interval of other activities' duration histograms, in order to display the horizontal axis more clearly.

An arresting point can still be discovered. Even if the organizer did not specify the duration of each standing/sitting acquisition segment, and the participants did not observe each other, the vast majority of participants still performed each standing and sitting at about 1 to 2 seconds using the pushbutton, and the overall duration statistics of these two activities are approximately normally distributed. Such phenomenons may involve a variety of topics such as behavioral science and natural psychological rhythm, which will not be expanded due to the different research fields.

4 CONCLUSIONS

Relying on the rigorous acquisition protocol design and execution, as well as the well-segmented data corpus of the recently released multimodal wearable sensor-based human activity dataset *CSL-SHARE*, this paper analyzes the duration statistics and distribution of 22 basic single motions of daily activities and sports, providing research references for human activity studies, such as segmentation, feature extraction, modeling, and recognition.

Through the big data statistical analysis of each activity's duration, we discovered that one single-motion activity or one cycle in the activities of cyclical motions has an average duration in the interval from about 1 second to 2 seconds.

Furthermore, the duration distribution histograms of each studied human daily activity or simple sports activity evince interindividual similarities and naturally obey a normal distribution. Even the two postures, standing and sitting, for which participants arbitrarily decided each segment's length, also conform to this observation unpredictably.

As a classic case of applying activity duration statistics in ML, (Liu and Schultz, 2019) used the previous dataset of *CSL-SHARE* with the same equipment and investigated the transition from the offline HAR modeling research to a real-time HAR system. The activity duration was utilized as one of the references to find the optimal balance between the online decoding window length, the window overlap length, and the recognition delay, endowing the real-time demonstration with a satisfactory performance and user experience.

We have noticed that different types of falling activities also show interindividual similarity in terms of duration, which is of great significance for human activity research based on internal sensing and external sensing, such as adopting HAR modeling for fall detection and recognition (Xue and Liu, 2021). Duration analysis of typical falling activities will be a valuable topic to explore in the future, given appropriate and adequate research materials.

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