Method for Comparing Long-term Daily Life using Long-duration Episodes

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ABSTRACT

Collecting lifelogs comprising data related to human life over a long period of time has progressed in recent years due to the widespread use of inexpensive small sensors. Understanding long-term daily life can be helpful in healthcare applications and for improving quality of life, for example. In this research, we propose a method for comparing two periods of daily life, which makes it possible to find similar and different life periods in lifelogs. Since a human life includes various behaviors, we propose an approach for comparing two periods of daily life based on the differences in the behaviors performed in each period. We extracted episodes corresponding to several behaviors from motion data acquired with wearable sensors. Frequent episodes corresponding to frequent behaviors can be extracted using conventional episode mining methods. However, when comparing daily lives, not only a behavior frequency, but also its duration is important. Hence, we introduce long-duration episodes corresponding to long-running behaviors. In the proposed method, the similarity of two daily life periods is calculated based on differences of long-duration and frequent episodes. We demonstrate with experiments using real-life data that the proposed method can establish the similarity between two periods of daily life correctly.

1 INTRODUCTION

The collection and utilization of lifelogs comprising long-term data about human life have advanced in recent years due to the widespread use of inexpensive and small sensors. For example, MyLifeBits is known as a research project focusing on lifelogs [11, 12]. In MyLifeBits, scans of photos, books, and letters, webpage browsing and e-commerce history, GPS position information, sent e-mails, and files of photos and videos are collected as lifelog. Users can look back on their lives by browsing their past data. Data continuously measured over a long period of time by wearable sensors can also constitute a lifelog [13]. For example, a small wristband or clip device with an acceleration sensor is often used to collect motion data, from which information such as the number of steps per day, calories burned, sleeping time, amount of exercise performed per a time unit, and heart rate can be derived and visualized.

Many studies have been reported on recognizing and visualizing human activities from lifelogs using data mining techniques [6, 8, 16, 27]. Lifelogs have also been utilized in healthcare[9] proposing applications for monitoring and improving diet[4, 10], smoking cessation[28], analyzing the effects of daily activities on disease progression [7, 23, 29]. One main goal in applying lifelogs to healthcare is expected to help us understand long-term life[14]. Lifelogs can help users remember past events. However, only browsing past data is insufficient for understanding long-term daily life. Knowing how a user spent past time, rather than what the user did in the past, can be useful for improving the user's daily life. The Social Rhythm Metric (SRM) method for evaluating the regularity of daily life over a long period was proposed by [24, 25]. The authors used questionnaires to collect times for 17 types of behaviors, including wakeup, breakfast, and commute times, and measured the life regularity based on the dispersion of these times. The limitation of this study is that users are required to record times manually, which is difficult to continue over a long period of time. Research to build human behavior model for user identification from lifelog of many sensors on smartphone has been reported in [18]. However, this model focuses on user identification, and it is not targeted for understanding one user's long-term daily life. An approach for monitoring and detecting life changes using lifelogs comprising movement and location collected by many room sensors has been reported in [26]. For applications of healthcare, it is necessary to consider not only daily behaviors of in the house but also that of outside the house.

To compare daily life over a few weeks, it should be characterized with the behaviors performed during this period. When many similar or different behaviors are exhibited in two distinct periods, these periods can be treated as having similar or different daily lives, respectively. Motion data acquired by a wristband device equipped with an acceleration sensor is used in this study to characterize human behavior as a series of events. Therefore, episodes corresponding to different behaviors can be established by applying an episode mining algorithm to motion data. For example, an episode mining algorithm proposed by [5, 19, 33] finds frequent episodes, while frequent episodes are regarded as those corresponding to frequently performed behaviors. Another algorithm for episode mining that consider the duration of events was proposed by [30, 32]. The limitation of these algorithms is that they cannot find long-duration behaviors, frequency of which is low, with duration as a threshold. High utility episode mining algorithms [31] have been proposed that consider weight of items in a dataset. By treating duration of an event as a weight, these algorithms can find an episode with duration threshold; however, these algorithms cannot find episodes corresponding to long-duration behaviors. We cannot duplicate the same behavior at the same time. These algorithms do not consider overlapping of occurrence intervals.

In this study, we propose an approach for comparing two periods of long-term daily life. We introduce a procedure for finding long-duration episodes by evaluating the sum of durations rather than the frequency of occurrence. We then compare two periods of daily life using both frequent and long-duration episodes extracted from the entire lifelog of motion data. To achieve this, we calculate the similarity between each pair of episodes that are locally long-duration or frequent in each period. The effectiveness of the proposed method is evaluated with experiments using real-life data.

2 COMPARISON OF DAILY LIVES

This study evaluates the similarity between two periods of daily life of one user. We assume that human life consists of various behaviors, which we define as a series of activities performed with purpose. For example, the daily life of a student during an academic term consists of behaviors such as going to school, taking classes, and studying. During the summer vacation period, the student's daily life consists of behaviors such as studying, working part-time, and hanging out with friends.

In this study, we compare two periods of daily life according to the difference of the behaviors the user performs during each period. Hence, the problem of daily life comparison can be formulated as comparing the similarity between a set of behaviors performed in periods 1 and 2. To characterize behaviors, motion data are used in this study.

3 LIFELOG DATA USED IN THIS PAPER

We used the life recorder UW-301BT from Hitachi Systems as a sensor device (Figure 1) to collect motion data. Three-axis acceleration of the arm movement was measured as the device was worn on the wrist during the day and while sleeping. The output of this device is motion status data indicating a segment, in which the same type of motion status continues. This data is continuously output without interruption or overlapping. The degree of activity intensity is expressed in the following nine types of motion statuses: "rest", "quiet (sitting quietly)", "deskwork (sitting task)", "light work (standing work)", "work", "exercise", "walking", "jogging", and "not-wearing". These statuses describe the intensity of activity level in order from "rest" to "exercise". "Walking" indicates that a periodic activity was performed. "Jogging" indicates that a periodic and hard activity was performed.

Figure 1: Wristband device UW-301BT

A motion status data $D = \langle d_1, \dots, d_n \rangle$ is an ordered list of motion status events. A motion status event $d_i = (m_j, T_{s_i}, T_{e_i})$ with $1 \leq i \leq n$ is a set consisting of a motion status, starting, and ending date-time. Here, $m_j \in M$ (M is a set of motion statuses) is a motion status. T_{s_i} and T_{e_i} are starting and ending date-time, where $T_{s_i} < T_{e_i}$ with $1 \leq i \leq n$ and $T_{e_i} \leq T_{s_{i+1}}$ with $1 \leq i \leq n-1$. The duration of motion status d_i is $T_{e_i} - T_{s_i}$. Table 1 shows an example of motion status events. The motion status event in the first row means that "walking" continued for 3 minutes from "2018-10-15 08:02" to "2018-10-15 08:05". The motion status event in the second row means that "deskwork" began soon after "walking". The motion status data consisting of motion status events in Table 1 are arranged in order of starting date-time: ⟨(walking, 2018-10-15 08:02, 2018-10-15 08:05), (deskwork, 2018-10-15 08:05, 2018-10-15 08:44), . . . , (light work, 2018-10-15 16:40, 2018-10-15 16:55)⟩.

Table 1: Example of motion status events

motion status	starting date-time	ending date-time
walking	2018-10-15 08:02	2018-10-15 08:05
deskwork	2018-10-15 08:05	2018-10-15 08:44
walking	2018-10-15 08:44	2018-10-15 08:56
deskwork	2018-10-15 08:56	2018-10-15 09:52
walking	2018-10-15 09:52	2018-10-15 09:59
light work	2018-10-15 09:59	2018-10-15 10:34
quiet	2018-10-15 10:34	2018-10-15 12:01
deskwork	2018-10-15 12:01	2018-10-15 12:53
walking	2018-10-15 12:53	2018-10-15 13:03
deskwork	2018-10-15 13:03	2018-10-15 14:25
walking	2018-10-15 14:25	2018-10-15 14:27
light work	2018-10-15 14:27	2018-10-15 14:47
deskwork	2018-10-15 14:47	2018-10-15 15:43
quiet	2018-10-15 15:43	2018-10-15 16:38
walking	2018-10-15 16:38	2018-10-15 16:40
light work	2018-10-15 16:40	2018-10-15 16:55

Conventional sensor devices equipped with an accelerometer do not output motion status data. The majority of such devices output the amount of activity per unit time as a time-series data. A method for detecting segments, in which characteristic activities are performed, from the amount of activity per unit time has been proposed [21]. Methods for generating symbolic representation of time-series data such as Symbolic Aggregate Approximation (SAX) [15] can also be used to obtain motion status data from the amount of activity per unit time.

4 BEHAVIOR AND MOTIONAL STATUS PATTERN

A behavior constituting a user's daily life is a series of activities performed with purpose. In other words, a behavior appears in the motion status data as an ordered pattern of some motion statuses. For example, consider the behavior of going shopping by walking from home to a store. This behavior consists of walking from home to the store, shopping in the store, and walking from the store to home. In the motion status data, this behavior appears as "walking", "light work", and "walking". In this way, behaviors can be expressed in the order of completion of corresponding motion statuses.

The motion status data represents a single event sequence, while the motion status pattern represents the order of motion statuses. Therefore, an episode extracted by applying episode mining to the motion status data corresponds to a pattern of the motion status indicating a behavior. Many episode mining methods have been proposed [1, 5, 17, 19, 20, 22, 30, 32, 33]. An episode showing a behavior of a user is suitable for representing the followed-by-closely pattern of ordered motion statuses. Note that a user cannot perform several motion statuses at the same time. In this paper, we adopt the serial episode with minimal and non-overlapping occurrences [17, 33].

We consider that frequent and long-duration episodes correspond to behaviors performed mundanely. Exceptional behaviors that are not normally performed can be identified by browsing the lifelog. However, these exceptional behaviors are not useful for comparing long periods of daily life, and hence are excluded in this study. In this study, we use a formalism of MANEPI [33] to identify frequent episodes. In addition, we define a new type of episodes, namely, long-duration episodes.

Episode: Let $\alpha = \langle m_1, \ldots, m_k \rangle$ be an episode, where $m_j \in M$. The length of α is the number of motion statuses. Episode refers to the ordered pattern, in which each motion status appears in the order from m_1 to m_k. An episode $\alpha = \langle m_1, \ldots, m_k \rangle$ is a sub-episode of another episode $\beta = \langle m'_1, \ldots, m'_s \rangle$ if there exists $1 \leq j_1 < \cdots < j_k \leq s$ such that $m_i = m'_{j_i}$ for all i with $1 \leq i \leq k$. For example, episode $\langle walking, deskwork, lightwork \rangle$ means that motion statuses appear in the order of "walking", "deskwork", and "light work". Episode $\langle walking, deskwork \rangle$ is a sub-episode of episode $\langle walking, deskwork, lightwork \rangle$.

Occurrence: In the motion status data D, if each motion status m_j of the episode α is contained in D preserving the order, it denotes that α appears in D. The occurrence of α, denoted by $occ(\alpha)$, is a segment, where α appears in D. $occ(\alpha)$ is denoted as $[T_{s_{m_1}}, T_{e_{m_k}}]$ using the starting date and time of a motion status event including m_1 and the ending date and time of a motion status event including m_k. The duration of $occ(\alpha) = [T_{s_{m_1}}, T_{e_{m_k}}]$ is $T_{e_{m_k}} - T_{s_{m_1}}$. In Table 1, one of the occurrences of episode $\alpha = \langle walking, deskwork, lightwork \rangle$ is $occ(\alpha)$ = [2018-10-15 08:44, 2018-10-15 10:34].

To exclude redundant occurrences where the duration required for one behavior becomes too long, we use a constraint related to the span of an occurrence [1, 30]. A span is defined by the duration or length of an occurrence. In this paper, we define a span by the duration of an occurrence since episodes correspond to behaviors. A span constraint, *maxspan*, is the upper bound of the duration of each occurrence[31]. An occurrence $occ(\alpha) = [T_s, T_e]$ of the episode α has to satisfy *maxspan* such that $T_e - T_s \leq maxspan$. For example, for episode $\alpha = \langle walking, deskwork, lightwork \rangle$, $occ(\alpha)$ = [2018-10-15 08:44, 2018-10-15 10:34] satisfies the constraint *maxspan* = 300 minutes; however, $occ(\alpha)$ = [2018-10-15 08:44, 2018-10-15 14:47] does not satisfied this constraint.

Moreover, we use a gap constraint, *maxgap*, that is the maximum length of the time interval between two consecutive motion status events in an occurrence [1, 22]. Let a segment of D be an occurrence of episode $\alpha = \langle m_1, \ldots, m_k \rangle$ if the time interval between the ending date-time of m_i and the starting date-time of m_{i+1} is *maxgap* or less for all i with $1 \leq i < k$. For example, $occ(\langle walking, deskwork, lightwork \rangle)$ = [2018-10-15 09:52, 2018-10-15 14:47] does not satisfy *maxgap* = 120 minutes because the time interval of motion status events corresponding to "walking" and "deskwork" is 122 minutes (= "2018-10-15 12:01" − "2018-10-15 09:59").

Among the occurrences of episode α, a set of all occurrences satisfying *maxspan* and *maxgap* is the occurrence list of α, denoted in this paper as $OCC(\alpha)$. In Table 1, the occurrence list of episode $\alpha = \langle walking, deskwork, lightwork \rangle$ satisfying *maxspan* = 300 minutes and *maxgap* = 120 minutes is $OCC(\alpha)$ = {[2018-10-15 08:02, 2018-10-15 10:34], [2018-10-15 08:44, 2018-10-15 10:34], [2018-10-15 12:53, 2018-10-15 14.47], [2018-10-15 12:53, 2018-10-15 16:55], [2018-10-15 14:25, 2018-10-15 16:55]}.

Minimal and non-overlapping occurrence: In this study, we consider episodes with minimal and non-overlapping occurrences [17, 33]. An occurrence of an episode α, $occ(\alpha)$, is minimal if $occ(\alpha)$ does not contain any other occurrences in $OCC(\alpha)$. For occurrences $[t_s, t_e], [t'_s, t'_e] \in OCC(\alpha)$, $[t'_s, t'_e]$ contains $[t_s, t_e]$ if $t_s \geq t'_s \wedge t_e \leq t'_e$. A set of minimal occurrences of episode α is denoted as $MO(\alpha)$. Here, $MO(\alpha) \subseteq OCC(\alpha)$. For example, in $OCC(\langle walking, deskwork, lightwork \rangle)$, [2018-10-15 08:02, 2018-10-15 10:34] is not minimal occurrence since it contains [2018-10-15 08:44, 2018-10-15 10:34]. Set of minimal occurrences of $\langle walking, deskwork, lightwork \rangle$ is $MO(\langle walking, deskwork, lightwork \rangle)$ = { [2018-10-15 08:44, 2018-10-15 10:34], [2018-10-15 12:53, 2018-10-15 14.47], [2018-10-15 14:25, 2018-10-15 16:55]}.

For occurrences $[t_s, t_e], [t'_s, t'_e] \in OCC(\alpha)$, the relationship is non-overlapping if $t_e < t'_s \vee t'_e < t_s$. A set of minimal and non-overlapping occurrences of episode α is denoted as $MAMO(\alpha)$. Here, $MAMO(\alpha) \subseteq MO(\alpha)$. When several occurrences overlap, we preferentially select the occurrence of the earliest possible starting date-time as *MAMO*. For example, in $MO(\langle walking, deskwork, lightwork \rangle)$, [2018-10-15 12:53, 2018-10-15 14:47] and [2018-10-15 14:25, 2018-10-15 16:55] are overlapped. Set of minimal and non-overlapping occurrences of $\langle walking, deskwork, lightwork \rangle$ is $MAMO(\langle walking, deskwork, lightwork \rangle)$ = { [2018-10-15 08:44, 2018-10-15 10:34], [2018-10-15 12:53, 2018-10-15 14:47]}.

Frequency and frequent episode:
The frequency of episode α, $freq(\alpha)$, is the number of occurrences in $MAMO(\alpha)$;

$$freq(\alpha) = |MAMO(\alpha)|.$$

For example, $freq(\langle walking, deskwork, lightwork \rangle) = 2$. An episode satisfying a user-specified minimum value of the frequency, $minfreq$, is called a frequent episode.

Total duration and long-duration episode: The sum of the durations of all occurrences contained in $MAMO(\alpha)$ is named as the total duration of α, denoted by $tdur(\alpha)$;

$$tdur(\alpha) = \sum_{[t_s, t_e] \in MAMO(\alpha)} (t_e - t_s).$$

For example, $tdur(\langle walking, deskwork, lightwork \rangle) = 224$ minutes. An episode satisfying a user-specified minimum value of the total duration, *mintdur*, is called a long-duration episode.

5 EXTRACTING FREQUENT AND LONG-DURATION EPISODES

The problem of mining frequent episodes can be formulated as extracting all episodes satisfying $minfreq$. In this paper, frequent episodes are extracted using MANEPI [33] that extracts frequent episodes with minimal and non-overlapping occurrences. MANEPI extends episodes by adding one motion status event to frequent episodes. By concatenating an occurrence of motion status m to all occurrences of frequent episode α, MANEPI generates the occurrence list of episode $\langle \alpha, m \rangle$, $OCC(\alpha, m)$. Here, an occurrence of α, $occ(\alpha) = [t_{\alpha_s}, t_{\alpha_e}]$, is concatenated to an occurrence of m, $occ(m) = [t_{m_s}, t_{m_e}]$, which satisfies the following three conditions:

- $t_{\alpha_e} \leq t_{m_s}$
- $t_{m_e} - t_{\alpha_s} \leq maxspan$
- $t_{m_s} - t_{\alpha_e} \leq maxgap$.

A set of minimal occurrences $MO(\alpha, m)$ is generated by deleting non-minimal occurrences from $OCC(\alpha, m)$. By selecting non-overlapping occurrences from $MO(\alpha, m)$, we can attain a set of minimal and non-overlapping occurrences $MAMO(\alpha, m)$. If $MAMO(\alpha, m)$ satisfies $minfreq$, $\langle \alpha, m \rangle$ is outputted as a frequent episode. This process of extending episodes is repeated. Redundant candidate episodes can be pruned because the downward closure for frequent episode mining [2, 3] holds.

The problem of mining long-duration episodes can be formulated as extracting all episodes satisfying $mintdur$. Long-duration episodes can be extracted in the same way as MANEPI. However, to extract all long-duration episodes, it is necessary to examine episodes which do not satisfy $minfreq$. A long-duration episode is an episode satisfying $mintdur$ and having an unbounded frequency. An episode that does not satisfy $minfreq$ can also be long-duration. Consider Table 1 with $minfreq = 3$ and $mintdur = 200$ minutes. For episode $\alpha = \langle walking, deskwork, lightwork \rangle$, $freq(\alpha) = 2$, and $tdur(\alpha) = 224$ minutes. α is not extracted by frequent episode mining, since α does not satisfy $minfreq$. However, α is a long-duration episode since α satisfies $mintdur$. In long-duration episode mining, we have to consider the total duration rather than frequency.

However, the Apriori property does not hold for the total duration. For episodes α and β (α is a sub-episode of β), the total duration of β may be longer than that of α. For example, in Table 1, $tdur(\langle walking, lightwork \rangle) = 81$ minutes and $tdur(\langle walking, deskwork, lightwork \rangle) = 224$ minutes. Even if α does not satisfy $mintdur$, β must be examined; therefore, pruning cannot be performed using the total duration to extract long-duration episodes. However, it is not necessary to examine all candidate episodes. For an episode that becomes a long-duration episode, the frequency is minimum when the duration of all occurrences is $maxspan$. In other words, the lower bound of the frequency of a long-duration episode is $\lceil \frac{mintdur}{maxspan} \rceil$. For example, when $mintdur = 1000$ minutes and $maxspan = 300$ minutes, an episode X such that $freq(X) < 4$ $(= \lceil \frac{1000}{300} \rceil)$ cannot be a long-duration episode. Therefore, it is sufficient to extract episodes with this lower bound of frequency in MANEPI. Hereafter, the minimum frequency in a long-duration episode mining is denoted as $lowfreq$:

$$lowfreq = \lceil \frac{mintdur}{maxspan} \rceil.$$

When an episode satisfying $lowfreq$ is extracted, it is output as a long-duration episode if it satisfies $mintdur$.

The procedure of our method for mining long-duration episodes is as follows.

Procedure ExtractLongDurationEpisodes(D, $minfreq$, $mintdur$, $maxspan$, $maxgap$)
Input: a motion status data D,
  a frequency threshold of an episode $minfreq$,
  a total duration threshold of an episode $mintdur$,
  a duration constraint of an occurrence $maxspan$,
  a gap constraint of an occurrence $maxgap$
Output: all long-duration episodes

```
1:  FI := All motion statuses that satisfy lowfreq
2:  Generate minimal occurrence list MO for each motion
    status in FI
3:  foreach motion status h ∈ FI do
4:     foreach motion status m ∈ FI do
5:        ExtendEpisode(h, m)
6:     end
7:  end
```

ExtendEpisode(α, m)
Input: episode α, motion status m
Output: long-duration episode β

```
8:  Generate episode β by appending m to α
9:  MO(β) = ∅
10: foreach occ [oa_s, oa_e] ∈ MO(α) do
11:    Extract the occurrence [om_s, om_e] ∈ MO(m)
       such that om_s < om'_s ∧ om_s ≥ oa_e ∧ om'_s > oa_e
       for any [om'_s, om'_e] ∈ MO(m)
12:    if (om_e − oa_s ≤ maxspan) ∧ (om_s − oa_e ≤ maxgap) then
13:       Append [oa_s, om_e] to MO(β)
14:    endif
15: end
16: Delete occ [o_s, o_e] from MO(β) such that o_e == o'_e ∧ o_s > o'_s
    for any [o_s, o_e], [o'_s, o'_e] ∈ MO(β)
17: MAMO(β) = ∅
18: foreach occ [o_s, o_e] ∈ MO(β) do
19:    if (o_s ≥ o'_e for any [o'_s, o'_e] ∈ MAMO(β)) then
20:       Append [o_s, o_e] to MAMO(β)
21:    endif
22: end
23: if |MAMO(β)| ≥ lowfreq then
24:    tdur(β) = Σ_{[o_s, o_e] ∈ MAMO(β)} (o_e − o_s)
25:    if tdur(β) ≥ mintdur then
26:       Output β as long-duration episode
27:    endif
28:    foreach motion status m' ∈ FI do
29:       ExtendEpisode(β, m')
30:    end
31: endif
```

The episode that satisfies $lowfreq$ can become a long-duration episode; hence, we have to examine episodes that satisfy $lowfreq$. First, all motion statuses that satisfy $lowfreq$ are extracted (line 1), and the minimal occurrence lists of these motion statuses are generated at the same time (line 2). Here, for a motion status m, $OCC(m)$ and $MO(m)$ are equivalent. Then, an episode extended with one motion status is examined in the ascending order of short episodes (line 3-7). We can extract all long-duration episodes using this procedure.

In ExtendEpisode procedure for extending episode α by motion status m, episode $\langle \beta \rangle = \langle \alpha, m \rangle$ is generated (line 8), occurrence of m is added to occurrences of α to generate the occurrence list of β (line 9-15), non-minimal occurrences are deleted (line 16), and the minimal occurrence list of β, $MO(\beta)$, is generated. Then, non-overlapping patterns are sequentially selected from the head of $MO(\beta)$ (line 17-22), and $MAMO(\beta)$ is generated. When $MAMO(\beta)$ satisfies the lower bound of frequency for long-duration episodes (line 23), the total duration of β is calculated (line 24). When the total duration of β satisfies the minimum threshold of the total duration (line 25), β is output as a long-duration episode (line 26). Since an episode that satisfies $lowfreq$ can become a long-duration episode, ExtendEpisode procedure is repeated (line 28-30).

6 PROPOSED METHOD

We compare two periods Pd_1 and Pd_2 of daily life by measuring their similarity based on motion status data D, minimum frequency $minfreq$, minimum total duration $mintdur$, maximum occurrence duration $maxspan$, and maximum gap $maxgap$.

We focus on behaviors performed mundanely in the user's daily life. First, long-duration and frequent episodes are extracted from the entire motion status data. In the two periods, episodes corresponding to actual behaviors are selected. Then, the similarity the two periods is evaluated based on the difference of the episodes included in each period. The procedure of the proposed method is as follows.

(1) Extracting global long-duration episodes and global frequent episodes:
Extract long-duration and frequent episodes from the entire motion status data D. We call these episodes as global long-duration and global frequent episodes, respectively. Non-maximal episodes are deleted from these global episodes. Here, a maximal episode is an episode that is not a sub-episode of any other episode.

(2) Taking out local long-duration episodes and local frequent episodes:
Episodes that are locally long-duration episodes and locally frequent episodes in each period are selected from their global counterparts. Locally long-duration and frequent episodes in a period Pd_i are long-duration and frequent episodes that satisfy long-duration and frequent conditions $mintdur$ and $minfreq$ in this period, respectively.
For each global long-duration or frequent episode g, all occurrences satisfying the following two conditions are selected from $MAMO(g)$:
- starting date-time of $occ(g) \geq$ date-time of the first day of period Pd_1,
- ending date-time of $occ(g) \leq$ date-time of the last day of period Pd_1.

When the total duration or frequency of the selected occurrences satisfies the relative $mintdur$ or $minfreq$ ratio of period Pd_i to the entire motion data, g is appended to LL_{Pd_i} or LF_{Pd_i}, respectively. Here, LL_{Pd_i} and LF_{Pd_i} are the sets of local long-duration and frequent episodes satisfying the relative condition in the period Pd_i.

(3) Evaluating similarity of daily lives:
The similarity between two periods is calculated from the set of their corresponding local long-duration and local frequent episodes using the Jaccard index.
Here, the Jaccard index is calculated as $\frac{|LL_{Pd_1} \cap LL_{Pd_2}| + |LF_{Pd_1} \cap LF_{Pd_2}|}{|LL_{Pd_1} \cup LL_{Pd_2}| + |LF_{Pd_1} \cup LF_{Pd_2}|}$, where LL_{Pd_i} is a set of local long-duration episodes of period Pd_i and LF_{Pd_i} is a set of local frequent episodes of period Pd_i; $i = 1, 2$.

In (1), long-duration and frequent episodes are extracted from the entire motion status data. These episodes are not extracted from the motion status data of each period to be compared. Although the considered comparison period is several weeks, $mintdur$ and $minfreq$ become too small in each period. Episodes that are long-duration or frequent only in the considered period are incidentally extracted. Therefore, episodes that do not correspond to daily behaviors may be extracted. Hence, we extract global long-duration episodes and global frequent episodes corresponding to daily behaviors from the entire motion status data.

Our method uses only maximal episodes to compare two periods of daily life since the similarity between these periods becomes high when using non-maximal episodes. Suppose there are episodes α and β corresponding to certain behaviors, and episode γ is a sub-episode of both α and β. Furthermore, episode α appears only in one of the two considered periods, while episode β appears only in the other period. Episode γ appears in both two periods. Let episodes α and β represent different behaviors in the two periods. Then, assuming that the two periods are similar would be incorrect since γ is a sub-episode of both α and β. However, episode γ becomes a factor to raise the similarity of two periods of daily life erroneously since γ appears in both periods. Hence, episode γ should not be considered as it is not an episode corresponding to a certain behavior. Therefore, only maximal episodes are considered in this study.

Our method compares two periods of daily life using local long-duration and frequent episodes in each period. In (2), all long-duration and frequent episodes are selected from global frequent and long-duration episodes, respectively. For example, consider the case where the entire motion status data period is 600 days, $minfreq$ is 1000, $mintdur$ is 72000 minutes, and the number of days in the period Pd is 30 days. When the total duration of the selected occurrences satisfies $7200 * \frac{30}{600}$, the episode is determined as local long-duration episode in period Pd and appended to LL_{Pd}. When the frequency of the selected occurrences satisfies $1000 * \frac{30}{600}$, the episode is determined as local frequent episode in period Pd and appended to LF_{Pd}.

In (3), our method outputs the Jaccard index as the similarity measure between two periods of daily life. When two periods are similar, the number of common long-duration and frequent episodes increases and the similarity becomes a value close to 1. On the other hand, when the user's daily life is different in the two periods, the similarity is close to 0.

7 EXPERIMENTS

We examine whether the proposed method can compare two periods of daily life using real-life data. In particular, we use motion status data collected from six participants. The period covered by each data set varies from 0.8 to 6.5 years (average is about 2.2 years). In this experiment, each motion status was divided into two motion statuses at the median of the duration. Five motion statuses, namely, "rest", "quiet", "deskwork", "light work", and "walking", were divided. Other motion statuses were not divided due to their low frequency. Therefore, the total number of motion statuses was 14.

We prepared 18 pairs of the periods in which similar daily lives were confirmed and 27 pairs of the periods in which different daily lives were confirmed. For each pair of the periods, their similarity was calculated using the proposed method. Here, we set the involved parameters as follows: $minfreq$ is 4 per week, $mintdur$ is 480 minutes per week, $maxspan$ is 240 minutes, and $maxgap$ is 45 minutes.

First, we evaluated the effect of using maximal episodes. Figures 2 and 3 show the similarity between the pair of periods evaluated using the proposed method with only maximal and all episodes, respectively.

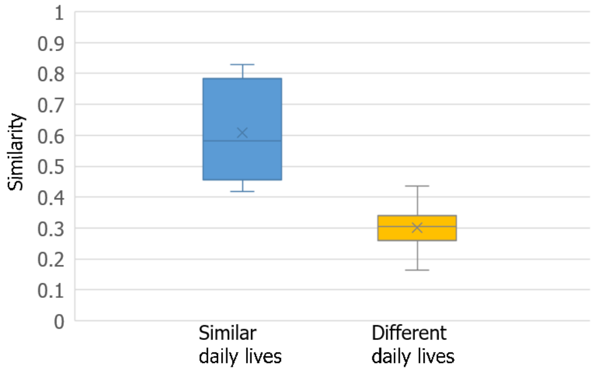

Figure 2: Similarity of two periods of daily life when using maximal long-duration and frequent episodes

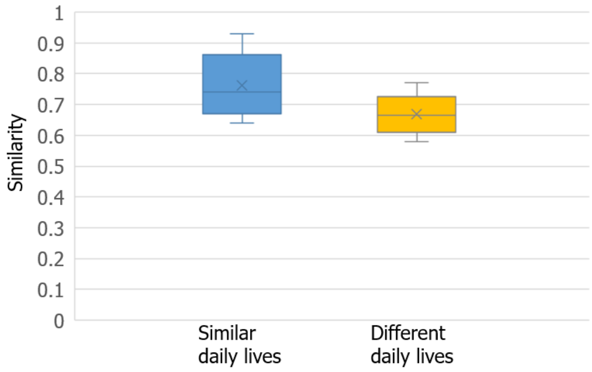

Figure 3: Similarity of two periods of daily life when using all long-duration and frequent episodes

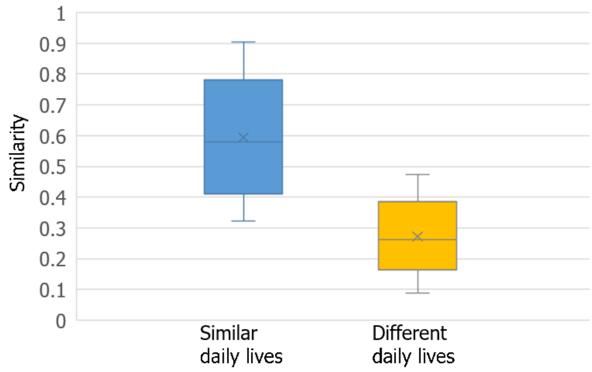

Figure 4: Similarity of two periods of daily life when using long-duration episodes

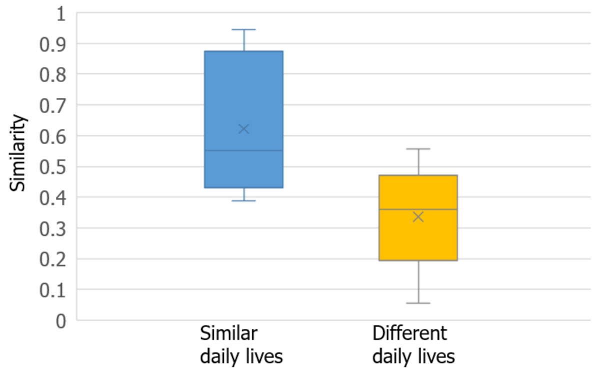

Figure 5: Similarity of two periods of daily life when using frequent episodes

It can be noticed from Figures 2 and 3 that the proposed method can compare two periods of daily life correctly. The similarity of the two periods, which the two respective subjects spent in the same way, is high, whereas that of different daily lives is low. When only maximal episodes are considered, the similarity of similar daily lives is higher than that of different daily lives. The error ratio, which we define as the ratio of cases in which the similarity of similar daily lives is smaller than that of different daily lives for each participant, was 0%. This means that the proposed method using only maximal episodes can compare two periods of daily life correctly. On the other hand, the similarity becomes high when all episodes are used even for different daily lives. The error ratio when using all episodes was 43%. This means that we cannot correctly compare daily lives in many cases when all episodes are used. Note that non-maximal episodes are included when considering all episodes. A non-maximal episode is a sub-episode of multiple maximal episodes. This means that a non-maximal episodes is a part of multiple behaviors. Therefore, even if a maximal episode is long-duration or frequent in one period, its sub-pattern often becomes long-duration or frequent in two different periods. This trend becomes higher as the length of an episode shortens.

Next, we evaluated the effect of using both long-duration and frequent episodes. Figures 4 and 5 show the similarity between two periods of daily life when using only long-duration or frequent episodes.

Figures 2, 4, and 5 show that the range of the similarity of daily lives increases when using only either long-duration or frequent episodes. In particular, there are cases when the difference between the similarity of similar daily lives and that of different daily lives is bigger providing that only long-duration episodes are used. However, the lowest similarity value of similar daily lives decreases, and the maximum similarity value of different daily lives increases, which results in wrong comparison of daily lives. The error ratios when using only either long-duration or frequent episodes were 0.9% and 8%, respectively. This means that daily lives cannot be compared correctly when using only one of the episode types. The most accurate results can be attained when using both long-duration and frequent episodes, even if accuracy for one of them is low.

8 CONCLUSIONS

In this study, we proposed a method for comparing two periods of daily life based on episode mining of a lifelog of motion data. Conventional episode mining algorithms can extract frequent episodes, which correspond to frequently occurring behaviors. To characterize a human daily life, behaviors lasting for a long period of time are also important. Hence, we proposed an algorithm for mining long-duration episodes, which are evaluated based on their total duration rather than frequency. In this way, long-duration episodes with low frequency can be extracted.

The proposed method for comparing two periods of daily life uses both long-duration episodes and frequent episodes. For global long-duration and global frequent episodes extracted from the entire motion data, local long-duration episodes and local frequent episodes are selected for each period. Then, the similarity between two periods of daily life is calculated based on the sets of local long-duration and local frequent episodes for each period. By using only maximal episodes, our method avoids using redundant episodes. Experimental results on real-life data showed that the proposed method can correctly compare periods of daily life.

In this paper, the time slot during which an episode persists is not considered. In the future, we plan to extend our method to distinguish episodes using time slots, during which a pattern persists.

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