Discovering Unusual Periodically Human Activity Patterns Through Fuzzy High Utility Rare Itemsets Mining

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Abstract. Monitoring the resident activities is a key goal to build a safe and convenient environment in a smart house system. One way to capture the activity is by installing motion sensors around the house. By collecting the triggered sensor state, we attempt to find unusual activity patterns to notify suspicious movements or health issues information as our main goals. This study focuses to express the nature of time interval of each activity more clearly using fuzzy set. Next, this study employs fuzzy high utility rare itemsets mining to obtain some odd activities with different quantity of time intervals. Hence, we can determine how peculiar the activity. In this study, we analyzed the public human activity recognition dataset based on each single resident and their activities. As the results, we successfully catch the uncommon activity compared to the daily ones either fishy movements or sick, the illogical movement order, and the false alarm due to the limitation of sensor transmission.

Keywords: Unusual Human Activity, Periodical Patterns, High Utility Itemsets, Fuzzy Itemsets.

1. Introduction

Internet of Things (IoT) has driven many governments to create smart city systems, e.g., smart factories and smart houses. From IoT, we enjoy a bunch of data collection from numerous different integrated sensors that convey many real-world problems. Speaking to smart house system, Human Activity Recognition (HAR) is a challenging task that we expect to find the solutions. By monitoring the activity patterns of the residents, we learn the current resident conditions to predict their future status. Consequently, we can offer a safe and convenient living experience in their residence(s) by knowing their situations in advanced. Motion or temperature sensors installation around the house, Inertial Measurement Unit (IMU) sensor in a smart watch, or surveillance cameras are alternative ways to capture the daily resident activities. A study about HAR based on motion sensor was conducted by T. L. M. Van Kasteren et al [1] using machine learning methods, i.e., naïve Bayes classifier, Hidden Markov Model (HMM) and conditional random fields (CRF). Beside machine learning, contrast sequence patterns mining (CSPM) as a data mining technique used to handle HAR case that studied by Iqbal and Pao [2]. They extended the CSPM to fit the multi-class nature and visualized both the resident movements and its activity label that easy to read for the user. However, they
only concentrated on recognizing the regular activities. As human motion may be represented in many viewpoints, this study will focus on revealing the hidden patterns on the historical resident activities as the first part of HAR thus the user can give their decision.

In general, human activities can be categorized into two: normal and abnormal (unusual) activities. This study goal is to extract unusual human or resident activity patterns which may included on warning system by showing suspicious actions or health issues. The idea to determine an activity called “unusual” is by looking its time interval in ”very short” term. Meanwhile, calculating the interval may hard to say whether very short since each activity will occur with variant time intervals. Therefore, this study defines the time interval of each activity using fuzzy set [3]. Also, this study employs Fuzzy High Utility Rare Itemsets Mining (FHURIM) [4] by computing the fuzzy support time interval of each itemset. As the outcomes, we draw the unusual activity pattern and user can understand its situation easily. In this study, we named the pattern as unusual periodically human activity patterns (UPHAP). Based on FHURIM, we also obtain very high and high UPHAP in one extraction by specifying two fuzzy support thresholds. For the remain organization of this paper is described as follows: section 2 shows some previous and related studies on HAR using data mining techniques, section 3 explains the mining process to get the unusual activity patterns, section 4 examines the UPHAP on the public HAR dataset and section 5 concludes the study results.

2. Related Works
HAR applications still open challenges for many researchers due to how the domain data from the ubiquitous sensors and extraction the useful pattern to describe the activity for the recognition. In this study, we prefer to play on motion sensor data and search its interesting activity patterns. Avci and Passerini (2012) [5] improved the recognition by segmenting the patterns to their activity label. Railean et al (2013) [6] examined the sequential patterns by proposing closeness preferences measurement. Ye et al (2014) [7] presented semantic mining on activity recognition by taking the ontology model. Yassien et al (2017) [8] studied to get patterns of routine activities of residents based on their electronic goods consumption that collected from smart meter within 24 hours. Mukhlash et al (2018) [9] considered time interval when finding the patterns using fuzzy set and sequential patterns mining resulting they hold periodically human activity patterns. However, they focus on obtaining regular activity patterns. When we speak a system, we also may want to find the rare activity pattern to warn the resident. Iqbal et al (2019) [10] recognized the rare human activity with fair precision results yet some regular activity pattern still can be found since its time interval consider short enough. To overcome the drawbacks, this study applies fuzzy high utility rare itemsets mining and defines the time interval of activity using fuzzy set.

3. Methodology
3.1. Preliminary
Given a database $D = \{(t_i, s_i, a_i) \mid t_i \in T, s_i \in S, a_i \in A\}$. Database $D$ consists of the time when the sensor was triggered $t_i$, the sensor label when was triggered $s_i$, and activity label when was triggered $a_i$. From database $D$, this study also provides information about the length of activity time based on sensor label provided using fuzzy. The time interval of an activity is categorized into three linguistic variables such as short (s), normal (n) and long (ℓ) in the set $F = \{s, n, ℓ\}$. 1 is the lowest value of activity time length and 2734 is the highest value of activity time length. We use triangular shaped function and we formulated the membership function of the three linguistic term $t_i$ as:
Figure 1: Membership Function of activity time length

\[ \mu_s(t_i) = \begin{cases} 1, & t_i \leq 1 \\ \frac{t_i - 1}{1366}, & 1 < t_i \leq 1367 \\ 0, & t_i > 1367 \end{cases} \]

\[ \mu_n(t_i) = \begin{cases} 0, & t_i \leq 1 \\ \frac{1367 - t_i}{1366}, & 1 < t_i \leq 1367 \\ 1367 - t_i, & 1367 < t_i \leq 2734 \\ 0, & t_i > 2734 \end{cases} \]

\[ \mu_{\ell}(t_i) = \begin{cases} 0, & t_i \leq 1367 \\ \frac{2734 - t_i}{1367}, & 1367 < t_i \leq 2734 \\ 1, & t_i > 2734 \end{cases} \] (1)

Furthermore, a set \( I = \{i_1, i_2, \ldots, i_n\} \) where \( I \subseteq S \times A \times F \) is the result of cross product between time interval of linguistic term, sensor label and activity label. Based on a database \( D \) and set of \( I \), we build a quantitative database \( Q = \{q_{ij} \mid |i_j|, i_j > D\} \) that contains the occurrence number of each itemset in \( I \). Next, we explain how to get the UPHAP using fuzzy high utility rare itemsets mining (FHURIM).

3.2. Fuzzy High Utility Rare Itemsets Mining on Human Activity Recognition

FHURI method has three main stages: (i) generating rare itemsets pattern, (ii) fuzzification of utility from each rare itemsets and (iii) very high and high utility rare itemsets pattern discovery. In generally, FHURI requires two support-related parameters to find the rare itemsets, which are \( \text{minlowSupp} \) dan \( \text{minverylowSupp} \). Meanwhile to find very high and high rare itemset patterns, two utility-related parameters are required, which are \( \text{minhighUtility} \) and \( \text{minveryhighUtility} \).

In the stage of generating rare itemsets pattern, infrequent human activity patterns are extracted from \( Q \) or pattern that has fuzzy support greater than two support-related parameters. As the results, we have a set of very low and low human activity patterns. At first level, we define five linguistic terms for the occurrence number of each itemset in \( Q \): \( I_{st} = \{\text{very-low} \)
(vl), low (l), normal (n), high (h), very-high (vh).}

\[
\mu_{i,j}(f_j) = \begin{cases} 
0, & f_j \leq a \\
\frac{f_j-a}{b-a}, & a < f_j \leq b \\
\frac{c-f_j}{c-b}, & b < f_j \leq c 
\end{cases} \tag{2}
\]

where, \(i, j \in I_{at}, 0 \leq a < b < c \leq \max(f_j)\) and \(f_j\) is frequency of item \(j\) in \(Q\). The value of \(a, b, c\) will be different depends of the itemsets length. Eq. 2 can be referred as fuzzy support from an itemset \(f_{supp}(i_j)\). Moreover, a fuzzy support of itemsets \(X\), can be formulated as follows:

\[
f_{supp}(X) = \sum_{i_j \in X, X \subseteq Q} f_{supp}(i_j); \tag{3}
\]

From eq. 3, fuzzy support of itemset candidate that appear is counted all. At the beginning of stage, two parameters are initialized, those are \(\text{minverylowSupp} \in [0, 1]\) and \(\text{minlowSupp} \in [0, 1]\) to determine number of unusual human activity patterns with 1-length or 1-rare itemsets. If \(f_{supp}(X) \leq \text{minverylowSupp}\) then 1-very low rare itemsets can be obtained and if \(f_{supp}(X) \leq \text{minlowSupp}\) then 1-low rare itemsets can be obtained.

After obtaining 1-rare itemsets or candidate itemsets \(C_1\), we count their fuzzy utility. Before that, we need to define five linguistic terms for the utility value of \(Q\): \(I_{at} = \{\text{very-low (vl)}, \text{low (l)}, \text{normal (n)}, \text{high (h)}, \text{very-high (vh)}\}\) where their membership function are given below.

\[
\mu_{i,j}(q_j) = \begin{cases} 
0, & q_j \leq d \\
\frac{q_j-d}{q_f-q_d}, & d < q_j \leq e \\
\frac{e-q_j}{e-f}, & e < q_j \leq f \\
0, & q_j > f 
\end{cases} \tag{4}
\]

where \(0 \leq d < e < f \leq \max(q_j)\). The value of \(d, e, f\) will be different depends of the itemsets length. Furthermore, eq. 4 they are called as fuzzy utility from an item in \(Q\) \(f_{util}(i_j, Q)\). While, fuzzy utility from an itemset \(X\) is formulated as:

\[
f_{util}(X) = \sum_{i_j \in X, X \subseteq Q} f_{util}(i_j, Q); \tag{5}
\]

In the stage of very high and high utility rare itemsets pattern discovery, two utility-related parameters \(\text{minveryhighUtility} \in [0, 1]\) and \(\text{minhighUtility} \in [0, 1]\) are initialized. From the candidate itemsets \(C_1\), if \(f_{util}(X) \geq \text{minveryhighUtility}\) then 1-very high rare itemsets pattern are obtained and if \(f_{util}(X) \geq \text{minhighUtility}\) then 1-high rare itemsets pattern are obtained, and those two patterns will be saved in set of \(L_1\). Furthermore, expansion of candidate will be done with 2-length \(C_2\) based on \(L_1\). If candidate itemsets \(C_2\) meet the criteria of high rare itemsets or very high rare itemsets then 2-rare itemsets will be obtained \((L_2)\). This expansion process will be done recursively till can not be found candidate rare itemsets or fuzzy support from candidate rare itemsets less than \(\text{minverylowSupp}\) and \(\text{minlowSupp}\). In general, the stages of mining unusual human activity pattern using FHURI method can be seen at Fig. 2.

4. Discussions

4.1. Data Information and Setups

This study uses secondary data [1] which publicly available for download from https://sites.google.com/site/tim0306/datasets. The information dataset is described as follows: the number of sensors on houseA, houseB and houseC are 14, 23, and 21, respectively. While, the
number of activity on houseA, houseB and houseC are 10, 13 and 16, respectively. Furthermore, the data collection process for the three shelters was carried out differently with details including houseA for 25 days, houseB for 14 days and houseC for 19 days. Next, we perform preprocessing data that consists three stages: 1) cleaning data by removing missing value data, 2) data discretization with $\Delta t = 60s$ (similar to [1]) and aggregation by integrating among sensor, activity labels and their time known as a set $I$, and 3) data transformation by creating a quantitative dataset $Q$ based on $I$. The details of the data preprocessing process are shown in Fig. 3.

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**Figure 2: Flow Chart of FHURIM**

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**Figure 3: The preprocesing data process**
4.2. Analysis Patterns for Single Residents

From quantitative database $Q$, we will search UPHAPs through FHURI method. In this study, will analyzing the historical data of occupants activity on house$A$, house$B$ and house$C$.

Table 1: Unusual human activity pattern from house$A$ when $\text{minSupp} = 1.0$ and $\text{minUtility} = 1.0$

| Pattern                              | cf | $\ell$ | $n$ | $h$ | $\ell h$ |
|--------------------------------------|----|--------|----|-----|----------|
| $[\text{bd, Pd, short ; kd, Pd, short ; tf, Pd, short}]$ | 0  | 0      | 0  | 1   | 0        |
| $[\text{kd, Pd, short ; Os, Pd, short ; bd, Pd, short ; tf, Pd, short ; cg, BT, short}]$ | 0  | 0      | 0  | 0   | 1        |
| $[\text{fd, OA, short ; kd, OA, short ; d, Pd, short ; cp, OA, short ; d, OA, short ; kd, Pd, short}]$ | 0  | 0      | 0  | 0   | 1        |
| $[\text{kd, OA, short ; kd, OA, short ; d, Pd, short ; pb1, OA, short ; cp, OA, short ; d, OA, short ; kd, Pd, short}]$ | 0  | 0      | 0  | 0   | 1        |
| $[\text{kd, OA, short ; kd, OA, short ; tf, OA, short ; d, Pd, short ; pb1, OA, short ; cp, OA, short ; d, OA, short ; kd, Pd, short}]$ | 0  | 0      | 0  | 0   | 1        |
| $[\text{kd, OA, short ; kd, OA, short ; d, Pd, short ; pb1, OA, short ; cp, OA, short ; d, OA, short ; cp, Pd, short ; kd, Pd, short}]$ | 0  | 0      | 0  | 0   | 1        |

Note: $\text{bd, Pd, short}$: balkondeur, Prepare dinner, short; $\text{kd, Pd, short}$: kwik dresser, Prepare dinner, short; $\text{tf, Pd, short}$: toilet flush, Prepare dinner, short; $\text{Os, Pd, short}$: Other sensor, Prepare dinner, short; $\text{cg, BT, short}$: cupboard groceries, Brush Teeth, short; $\text{fd, OA, short}$: frontdoor, Other Activity, short; $\text{kd, OA, short}$: kwik dresser, Other Activity, short; $\text{d, Pd, short}$: dead, Prepare dinner, short; $\text{cp, OA, short}$: cupboard plates, Other Activity, short; $\text{d, OA, short}$: dead, Other Activity, short; $\text{tf, OA, short}$: toilet flush, Other Activity, short; $\text{pb1, OA, short}$: press bed links, Other Activity, short; $\text{cp, Pd, short}$: cupboard plates, Prepare dinner, short.

To analyze UPHAPs on house$A$, threshold $0.5 \leq \text{minSupp} \leq 1$ and $0.4 \leq \text{minUtility} \leq 1$ will be used. After $\text{minSupp} \geq 0.8$, the number of rare itemset patterns has decreased drastically as we can see in Fig. 4 (a). And for $0.4 \leq \text{minUtility} \leq 1$, the greater the $\text{minUtility}$ value, the smaller the number of high utility itemset patterns produced as we can see in Fig. 4 (b). In other words, the number of patterns generated is inversely proportional to the given threshold values.

![Figure 4: Comparison of the number of patterns generated from houseA against threshold (a) minSupp and (b) minUtility.](image)

For threshold $\text{minSupp} = 1.0$ and $\text{minUtility} = 1.0$, UPHAPs from house$A$ are shown on Tab. 1. Based on criteria of high rare itemset and very high rare itemset patterns, there are five patterns of high utility rare itemset and one pattern of very high utility rare itemset. The difference between high utility rare itemsets and very high utility rare itemsets is the length

\[ \text{minlowSupp} = \text{minverylowSupp} = \text{minSupp} \]
\[ \text{minhighUtility} = \text{minveryhighUtility} = \text{minUtility} \]
of time as a utility of an unusual activity pattern. Thus, the very high rare itemsets pattern is an unusual pattern with very high time intervals compared to the high rare itemsets pattern. From high utility rare itemsets, we discover activity **prepare dinner** happen at **balkondeur** in a **short** for three consecutive incidents. While very high utility rare itemsets, we discover unusual human activity patterns with maximum in 8-length, namely activity of **Other activity** happen at **frontdoor** then at **kwik dresser** in a **short** both are continued by **prepare dinner** that happen in **dead** in a **short** then continued by **Other activity** consecutive happen in **press bed links, cupboard plates**, and **dead** in a **short** continued by **Prepare dinner** consecutive happen in **cupboard plate** and **kwik dresser** in a **short**. As we can see that there are unusual activities that are not happening where they should be or normally occurring, for example **prepare dinner** should be done at **fride, cupboard plate or toaster** not in **toiler flush** or **kwik dresser**. Then, There are also many unnamed activities that could be interpreted as suspicious activity at some point in time. In addition, there are several things that cause unusual occupant activities, as follows:

- An interruption occurred during the process of transmitting the sensor state when it was triggered.
- There are activities from other individuals than the occupants that trigger the sensors.

| Pattern | very low | low | normal | high | very high |
|---------|---------|-----|--------|------|-----------|
| [m,BT; m,GTB,s; m,PB,s; TD,GTB,s; m,LtH,s] | 0 | 0 | 0.034... | 0.965... | 0 |
| [m,BT; m,GTB,s; m,PB,s; TD,GTB,s; m,TS,s] | 0 | 0 | 0.034... | 0.965... | 0 |
| [m,BT; m,GTB,s; m,TS,s; TD,GTB,s; m,LtH,s] | 0 | 0 | 0 | 0 | 1 |

Note: M,BT,s : magnetron, Brush Teeth, short; M,GTB,s : magnetron, Go to bed, short; M,PB,s : magnetron, Prepare Brunch, short; TD,GTB,s : Toilet door, Go to bed, short; M,LtH,s : magnetron, Leaving the House, short; M,TS,s : magnetron, Take Shower, short

Furthermore, the analysis of UPHAP in **houseB**. Threshold that we use are 0.5 ≤ minSupp ≤ 1 and 0.4 ≤ minUtility ≤ 1. From Fig. 5, the number of rare itemset pattern decrease drastically when minSupp ≥ 0.6 and as long as minUtility goes up, then the number of high utility rare itemset pattern is decreasing. However, In the analysis of **houseB**, there is a limitation of the pattern generation with a maximum length of up to 6 which is called the truncated process. This is due to the explosion in the process of generating rare itemset candidate patterns in **houseB** which consume memory usage or out of memory.

For minSupp = 1.0 and minUtility = 0.9, there are high utility rare itemset patterns with the sensor being triggered is magnetron with the activity are brush teeth, go to bed and prepare brunch in a short then continued by go to bed that happen in toilet door in a short then continued by leaving the house with the triggered sensor is magnetron in a short. From the sequence of activities indicates that there is an unusual activity pattern from go to bed then prepare brunch then go to bed. It can be assumed that the occupants are sick and need a break because they are late for breakfast (brunch) and go back to sleep. While one of the very high rare itemset patterns are the magnetron sensor for several activities, i.e., brush teeth, go to bed, take shower in a short continued by go to bed happen in toilet door in a short continued by leaving the house with the triggered sensor is magnetron in a short. As we can see that the activity of occupant of **houseB** is normal activity but the triggered sensor is identified from the same sensor which allows false alarm. Overall, there was something unusual in that almost all activity on **houseB** was detected coming from the magnetron sensor. There are several things that cause unusual events at **houseB**, as follows:
Figure 5: Comparison of the number of patterns generated from houseB against threshold (a) $minSupp$ and (b) $minUtility$.

- the occurrence of transmissions that overlap or occur simultaneously, thus the recognized sensor is the first turned on sensor, namely the magnetron sensor
- magnetron sensor has an active duration longer than the other sensors, hence overlapping occurs which results in some occupant activities being only detected from the magnetron sensor

Some UPHAPs from houseB can be seen in Tab. 2.

Analysis of UPHAP from houseC also use the threshold of $0.5 \leq minSupp \leq 1$ and $0.4 \leq minUtility \leq 1$. It almost same with the analysis in houseB that the number of rare itemset patterns decrease drastically when $minSupp \geq 0.6$. with as long as $minUtility$ value goes up, then the number of high rare itemset will decrease.

Figure 6: Comparison of the number of patterns generated from houseC against threshold (a) $minSupp$ and (b) $minUtility$.

When $minSupp = 1.0$ and $minUtility = 1.0$, the result of very high rare itemset patterns is prepare lunch in koelkast, reed in a short continued by prepare breakfast in koelkast, reed in a short continued by shaving in backup in a short continued by use toilet upstairs in toilet flush boven in a short continued by prepare breakfast in magnetro reet in a short as we can see in Tab. 3. The sequence of activity is a mistake because the activity...
Table 3: UPHAPs *houseC* when the threshold $minSupp = 1.0$ and $minUtility = 1.0$

| Pattern | very low | low | normal | high | very high |
|---------|----------|-----|--------|------|----------|
| $[k, r, PL, s; k, r, PB, s; b, p, S, s; tlb, f, UTU, s; m, r, PB, s]$ | 0 | 0 | 0 | 0 | 1 |
| $[b, p, S, s; wlb, f, S, s; b, p, R, s; d, p, S, s; ds, Gd, s]$ | 0 | 0 | 0 | 0 | 1 |
| $[k, r, PL, s; k, r, PB, s; b, p, S, s; tlb, f, UTU, s; dtb, R, s]$ | 0 | 0 | 0 | 0 | 1 |
| $[b, p, S, s; wb, f, S, s; b, p, R, s; tlb, f, UTU, s; m, r, PB, s]$ | 0 | 0 | 0 | 0 | 1 |
| $[k, r, PL, s; k, r, PB, s; b, p, S, s; tlb, f, UTU, s; m, r, PB, s]$ | 0 | 0 | 0 | 0 | 1 |
| $[k, r, PL, s; k, r, PB, s; b, p, S, s; tlb, f, UTU, s; dtb, R, s]$ | 0 | 0 | 0 | 0 | 1 |
| ... | ... | ... | ... | ... | ... |

Note: $K, r, PL, S$ : Koelkast, reed,Prepare Lunch,Short; $K, r, PB, S$ : Koelkast,reed,Prepare Breakfast,short; $B, p, S, s$ : badkuip, pir,Shaving,short; $Tfb, f, UTU, s$ : toilet flush boven, flush,Use Toilet Upstairs,short; $Wb, f, S, s$ : wasbak boven, flush,Shaving,short; $B, p, R, s$ : badkuip, pir,Relax,short; $Tfb, f, UTU, s$ : toilet flush boven, flush,Use Toilet Upstairs,short; $M, r, PB, s$ : magnetron, reed,Prepare Breakfast,short; $D, p, S, s$ : dresser, pir,Shaving,short; $Dtb, R, s$ : deur toilet beneden,Relax,short; $Ds, Gd, s$ : deur slaapkamer,Get dressed,short; $Mbl, d, Gtb, s$ : mat bed links, drukmat,Go to bed,short

begins with lunch followed by breakfast activity. Furthermore, prepare breakfast and prepare lunch appear as *very high utility rare itemsets* which indicates that the occupant of *houseC* very rarely prepare breakfast or lunch at home. Other that, use toilet upstairs detected from the sensor *toilet flush boven* which indicates that the toilet upstairs is rarely used. On the other hand, there is activity that is detected by several sensors, which is *shaving* which is detected by sensors such as: badkuip, pir (bathtub), wasbak boven (sink upstairs), flush, or dresser, pir (wardrobe). It can be assumed that the occupant while doing shaving also do other activities (in dresser pear) or look for several positions (mostly in the bathroom area) which are rarely done in his daily life.

4.3. Analysis Patterns on housing

From the analysis of UPHAP from *houseA*, *houseB*, and *houseC*, then analyzed the activity patterns of the three occupants. Due to the different data collection dates for the three occupations, a database was formed starting from the earlier date to the most recent data collection date. We use the threshold $0.5 \leq minSupp \leq 1$ and $0.4 \leq minUtility \leq 1$. From Fig. 7, indicated that as long as the given $minSupp$, the number of rare itemset pattern doesn’t change. While, as in general the smaller $minUtility$ value then the more high utility rare itemsets can be obtained.

![Figure 7: Comparison of the number of patterns generated from houseC against threshold (a) $minSupp$ and (b) $minUtility$.](image-url)
With \( \text{minSupp} = 1.0 \) and \( \text{minUtility} = 0.9 \), there are patterns that can be said as high utility rare itemsets and very high utility rare itemsets. One of that is use toilet in balkeun deur in a short continued by go to bed in balkeun deur in a short continued by brush teeth in press bed recths in a short because this pattern has high fuzzy utility and very high fuzzy utility greater than 0.9. In other words, This pattern was rarely occured by the three occupants due to brushing their teeth before going to bed. Other that, one of the very high rare itemset pattern is prepare dinner with the triggered sensor are other sensor, kwik dresser, balkeun deur and toilet flush in a short continued by take shower in toilet flush in a short continued by Brush teeth in cupboard groceries in a short. Some high and very high utility rare itemset patterns can be seen at Tab. 4.

Table 4: UPHAPs from combined house when the threshold \( \text{minSupp} = 1.0 \) and \( \text{minUtility} = 0.9 \)

| Pattern | low | normal | high | very high |
|---------|-----|--------|------|-----------|
| \([\text{bd,UT,s};\text{bd,GtB,s};\text{pbr,BT,s}]\) | 0.002... | 0.997... | 0   |
| \([\text{bd,UT,s};\text{bd,GtB,s};\text{pbr,GtB,s}]\) | 0.002... | 0.997... | 0   |
| \([\text{bd,UT,s};\text{bd,GtB,s};\text{m,Gad,s}]\) | 0.002... | 0.997... | 0   |
| \([\text{OS,Pd,s};\text{Kd,Pd,s};\text{bd,Pd,s};\text{tf,LH,s};\text{cg,BT,s}]\) | 0.016... | 0.983... | 0   |
| \([\text{OS,Pd,s};\text{Kd,Pd,s};\text{bd,Pd,s};\text{tf,Pd,s};\text{tf,TS,s};\text{cg,BT,s}]\) | 0.016... | 0.983... | 0   |
| \([\text{OS,Pd,s};\text{Kd,Pd,s};\text{bd,Pd,s};\text{tf,Pd,s};\text{ti,TS,s};\text{cg,BT,s}]\) | 0.016... | 0.983... | 0   |

Note : Bd,UT,s : Balkon deur,Use Toilet,short; Bd,GtB,s : balkon deur,Go to bed,short; Pbr,BT,s : press bed recths,Go to bed,short; M,Gad,s : magnetron,Get a drink,short; OS,Pd,s : Other Sensor,Prepare dinner,short; Kd,Pd,s : Kwik dresser,Prepare dinner,short; Bd,Pd,s : Balkon deur,Prepare dinner,short; Tf,Pd,s : toilet flush,Prepare dinner,short; Tf,LH,s : toilet flush,Leaving the House,short; Cg,BT,s : cupboard groceries,Brush Teeth,short; OS,Pd,s : Other Sensor,Prepare dinner,short; D,PB,s : dead,Prepare Brunch,short; Tf,TS,s : toilet flush,Take Shower,short

5. Conclusions
This study mines human activity patterns that say unusual since its time interval is very short. Here, we called the patterns as unusual periodically human activity patterns (UPHAP). To obtain UPHAP, this study applies fuzzy high utility rate itemsets mining (FHURIM) method and defines fuzzy time interval of each activity and fuzzy support itemsets. From FHURIM, we can obtain very high and high UPHAP. By setting two parameters: \( \text{minSupp} \) and \( \text{minFuzzy} \), the number of UPHAP is increased when both \( \text{minSupp} \) and \( \text{minFuzzy} \) values are decreased. In the experiments, we analyzed the UPHAP of each resident in three different residences and the whole residents activities. As the results, we discover several UPHAP types: sick, suspicious activities, illogical movements order, and false alarm due to the limitation of sensor transmission. For future work, we need to deal with the missing value when the sensor transmission disrupted using rough set thus false alarm can be avoided.

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