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Mining Non-Zero-Rare Sequential Patterns on Activity Recognition

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Abstrak: Penemuan pola langka aktivitas manusia yang diperoleh dari sensor gerak yang aktif dapat memberikan informasi yang tidak biasa untuk memberitahukan seseorang dalam keadaan yang berbahaya. Penelitian ini bertujuan untuk mengenali aktivitas manusia yang langka menggunakan teknik penambangan pola *non-zero-rare* sekuensial. Pola tersebut harus muncul pada barisan sensor yang aktif dan jumlah kemunculannya tidak melebihi ambang batas kemunculan yang telah ditentukan sebelumnya. Penelitian ini mengusulkan sebuah algoritma untuk menambang pola *non-zero-rare* aktivitas manusia yang disebut ***M****ining* ***M****ulti-class Non-Zero-***R****are* ***S****equential* ***P****atterns* (MMRSP). Hasil eksperimen menunjukkan bahwa pola *non-zero-rare* aktivitas manusia mampu menangkap aktivitas yang tidak biasa. Selanjtunya, MMRSP bekerja dengan baik berdasarkan hasil nilai *precision* dari aktivitas yang jarang.

Kata kunci: *Pola Sekuensial, Pola Langka, Pengenalan Aktivitas. Multi-Kelas*

Abstract: Discovering rare human activity patterns—from triggered motion sensors deliver peculiar information to notify people about hazard situations. This study aims to recognize rare human activities using mining non-zero-rare sequential patterns technique. In particular, this study mines the triggered motion sensor sequences to obtain non-zero-rare human activity patterns—the patterns which most occur in the motion sensor sequences and the occurrence numbers are less than the pre-defined occurrence threshold. This study proposes an algorithm to mine non-zero-rare pattern on human activity recognition called **M**ining **M**ulti-class Non-Zero-**R**are **S**equential **P**atterns (MMRSP). The experimental result showed that non-zero-rare human activity patterns succeed to capture the unusual activity. Furthermore, the MMRSP performed well according to the precision value of rare activities.

Keywords: *Sequential Patterns, Rare Patterns, Activity Recognition, Multi-class.*

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1. Introduction

Discovering human activity patterns can help human life in better ways. We further plan to build a pleasant and safe living place by installing motion sensors in a house or apartment. In specific, we capture resident daily motions when the sensors are triggered. By collecting the triggered sensors sequences, we attempt to generate the triggered sensors patterns which can be used to understand the resident activities. However, understanding human activities from motion sensors are difficult and still being developed by finding its useful patterns. Machine learning and data mining are preferable techniques to uncover these useful patterns.

Kasteren *et al.* [1] used Hidden Markov Model (HMM) to classify the sensor sequences into several resident activities. Some other machine learning methods, such as naïve Bayes, Conditional Random Forest (CRF), and Support Vector Machines (SVM) was utilized in Cook *et al.* [2]. However, they did not present the generated model that clearly describes what is happening on the triggered sensors, lie what we may directly interpret in this paper. Therefore, this study employs sequential pattern mining to offer useful information about the patterns in $\boldsymbol{s} \rightarrow a$ form, where $\boldsymbol{s}$ and a denote a sensor sequence and a human activity, respectively. Iqbal and Pao [3], and Mukhlash *et al.* [4] studied several human activities types that can be considered as a typical pattern.

This study focuses on one type of rare patterns, so-called non-zero-rare patterns [5,6]. The goal of this study is to provide a rare human activity pattern which can inform the resident in hazard condition. We argue that the generated patterns may not represent the whole activities, if they only consider the occurrence pattern in the whole activity sequences, since the dataset may have several activities as the labels. Thus, we present a non-zero-rare human activity pattern as a subsequence, which must occur in sequences of one activity with the occurrence number is less than a pre-defined occurrence threshold. We propose an algorithm to mine non-zero-rare human activity pattern called Mining Multi-class Non-Zero-Rare Sequential Patterns (MMRSP). Based on the MMRSP, we obtain a non-zero pattern for each activity that differs from the previous works [5,6]. As far as we are aware, there is a limited number of research that discusses rare patterns on human activity recognition.

The organization of this paper describes as follows: Section 2 explains about mining sequential patterns techniques, especially on human activity recognition. The explanation about the non-zero-rare human activity pattern and the mining technique of the proposed method will be presented in Section 3. In Section 4 and Section 5, we discuss the experimental results and conclude the discussion, consecutively.

2. Related Works

Like the abovementioned, there are two previous works on human activity recognition using sequential pattern mining. In [3], a distinguishing subsequence on the multi-class classification proposed to recognize a distinguish sensor subsequence that is frequent in one activity sequences yet rarely in other sequences based on two support thresholds. They extended the idea in [7] using one-vs-all strategy. Mukhlash *et al.* [4] introduced a periodic human activity pattern. Thus we know about regular activity in a certain time interval using FP-Growth Prefix-Span and fuzzy theory to discretize the time interval. Also, there are several studies on human activity recognition using sequential pattern mining. A sensor pattern that significantly distinguishes from one to other activities was studied in [8]. Furthermore, frequent pattern mining based on multiple order temporal information was performed in [9], and weighted frequent patterns mining was proposed by [10] to adapt with classification task. We could say that those studies still focusing on typical activity patterns. Concerning about environmental safety, we also need to take a rare pattern into our consideration to deliver a quick alert that may put the resident may in the unpredicted situation.

This study discusses a non-zero-rare pattern based on [5,6] into human activity recognition. Since there are more than two activities, we extend the definition of the non-zero-rare pattern on the multi-class case. Also, we propose an algorithm to mine the non-zero-rare pattern on multi-class based on [11].

3. Mining Multi-class Non-Zero-Rare Sequential Patterns on Human Activity Recognition

In this section, we define the non-zero-rare-pattern on human activity recognition and describe an algorithm to mine the patterns.

3.1 Multi-class Non-Zero-Rare Sequential Patterns

First, we define a non-zero-rare human activity pattern. Assume that we have pairs of motion sensor sequences and human activity set $D = \{(\boldsymbol{s}_i, a_i) | \boldsymbol{s}_i \in S, a_i \in A, 1 \leq i \leq |D|\}$. A set of motion sensor sequences $S = \{\boldsymbol{s}_j | \boldsymbol{s}_j = (s_{j_1}, s_{j_2}, \cdots, s_{j_n}), s_{j_n} \in R \times M, 1 \leq j \leq n \leq |S|\}$, is collected when the sensors are triggered during t^{th}-time intervals with the sequence $\boldsymbol{s}_i$ which a result of Cartesian product between a set of motion sensor types $M = \{m_1, m_2, \cdots, m_{|M|}\}$ and a set of sensor location $R = \{r_1, r_2, \cdots, r_{|R|}\}$. For each time interval, a triggered sensor sequence belongs to a certain human activity label $a_k \in A$, where $A = \{a_1, a_2, \cdots, a_{|A|}\}$ is a set of human activity labels.

Let $\boldsymbol{s}_m = (s_{m_1}, s_{m_2}, \cdots, s_{m_\ell})$ be a subsequence of $\boldsymbol{s}_j$ $(\boldsymbol{s}_m \sqsubseteq \boldsymbol{s}_j, 1 \leq m_\ell \leq j \leq |\boldsymbol{s}_j|)$ and $supp(\boldsymbol{s}_m, D_{a_k}) = \frac{|\{s_j \preccurlyeq s_m | s_j \in D_{a_k}\}|}{|s_{a_k}|}$ be a relative support value of the subsequence $\boldsymbol{s}_m$ in D_{a_k}, Which can be used to extract rare patterns *w.r.t.* A certain activity label. Thus, we define $\boldsymbol{s}_m$ as a non-zero-rare sequential pattern for each activity below.

Definition 3.1. (A non-zero-rare human activity pattern)
Given a pre-defined support threshold γ, and a set of pairs of sensor sequence and human activity label D, A subsequence $\boldsymbol{s}_m$ is a non-zero-rare pattern on human activity label a_k or $(\boldsymbol{s}_m \rightarrow a_k)$ if and only if $\boldsymbol{s}_m$ satisfies $supp(\boldsymbol{s}_m, D_{a_k}) > 0$ and $supp(\boldsymbol{s}_m, D_{a_k}) < \gamma$.

In this study, we can say a pattern $\boldsymbol{s}_m$ *w.r.t.* an activity label a_k as a rule $(\boldsymbol{s}_m \rightarrow a_k)$. The rule form can be employed into the classification task. Furthermore, this study meets a multi-class classification problem since $|A| > 2$. We may use a traditional way, i.e., binary classification strategies to fit with a multi-class problem. There are two general binary classification strategies on the multi-class problem, such as *one-vs-all* (OVA), and *one-vs-one* (OVO). Both strategies may have better performance in some cases—accuracy result, but they are computationally expensive since both of them need to compare each positive class with the negative classes. Consequently, we extend **Definition 3.1.** by checking whether the maximum support value of $\boldsymbol{s}_m$ for each activity, label is less than a pre-defined support threshold γ and greater than 0.

Definition 3.2. (A multi-class non-zero-rare human activity pattern)
Given a pre-defined support threshold γ, and a set of pairs of sensor sequence and human activity label D, A subsequence $\boldsymbol{s}_m$ is a non-zero-rare pattern on human activity label a_k if and only if $\boldsymbol{s}_m$ satisfies $0 < \max_k\{supp(\boldsymbol{s}_m, S_{a_k}) | \forall a_k \in A\} = supp(\boldsymbol{s}_m, D_{a_k}) < \gamma$.

Table 1. An example of motion sensor sequences and its activity label set.

Event	Motion Sensor Sequence	Activity label
t_1	m_4, m_1, m_2, m_3	a_1
t_2	m_1, m_3, m_2, m_3	a_1
t_3	m_1, m_2, m_3	a_1
t_4	m_1, m_3, m_2	a_2
t_5	m_1, m_3	a_2

Example 3.1.
Assume we have a dataset D as shown in **Table 1.** and a pre-defined support threshold $\gamma = \frac{4}{5}$. A subsequence $\boldsymbol{s}_m = (m_1, m_2, m_3)$ is a non-zero-rare pattern for activity a_1 since $0 < \max\left(supp\left(\boldsymbol{s}_m, S_{a_k}\right), \forall a_k \in \{a_1, a_2\}\right) = supp\left(\boldsymbol{s}_m, S_{a_1}\right) = \frac{2}{3} < \gamma$.

According to **Definition 3.2.**, we do not need to perform two stages the classifier from the generated pattern, which is the basic procedures of mining sequential pattern techniques for classification case. Therefore, we can have an efficient algorithm as we directly build the rules (not only the patterns). In the next section, we will explain how to mine multi-class non-zero-rare human activity patterns.

3.2 Mining Non-Zero-Rare Sequential Patterns Algorithm

This study presents an algorithm to mine a multi-class non-zero-rare pattern called **M**ining **M**ulti-class Non-Zero-**R**are **S**equential **P**atterns (MMRSP). The MMRSP consists of two main stages, (1) *Rare Sequential Patterns Builder* (RSPB) and (2) *Classification Unseen Sequence* (CUS). **Algorithm 1** presents the detailed procedure of RSPB to build a non-zero-rare pattern based on a training set (L), where $(L \subseteq D)$. By the frequent subsequence mining techniques used in [11,12], we first generate a motion sensor type subsequences tree (lines 5,11). Then, the support values of each pattern in each activity sequences are calculated (line 7). The maximum support value is being checked to decide whether it is a non-zero-rare pattern (lines 8-9). Later, its activity label becomes the class or be placed in the consequent part if the subsequence is a non-zero-rare pattern. Additionally, we do not append the leaves node according to the *max-pruning strategy* in [7]. Otherwise, a single sensor type m from a set M is added into the left node until all the possible candidate subsequences no longer satisfying the frequent conditions [12].

Algorithm 1. (Rare Sequential Patterns Builder)

Input: a training set (L), a pre-defined support threshold (γ), a set of activity labels (A), and a sequence $(\boldsymbol{c})$

Procedure RSPB $(L, A, \gamma, \boldsymbol{c})$
1. $S_m = \emptyset$;
2. **for** each $a_k \in A$ **do**
3. $D_{a_k} = \{(\boldsymbol{s}_j \to a_k) | \boldsymbol{s}_j \in S\}$;
4.   **for** each $m \in R \times M$ **do**
5.   **if** $(\boldsymbol{c} \circ m) \not\supseteq S_m$ **then**
6. $\boldsymbol{mc} = \boldsymbol{c} \circ m$;
7.   count $supp(\boldsymbol{mc}, D_{a_k})$;
8.   **if** $0 < supp(\boldsymbol{mc}, D_{a_k}) < \gamma$ **then**
9. $S_m = S_m \cup (\boldsymbol{mc} \to a_k)$;
10.   **else if** $supp(\boldsymbol{mc}, D_{a_k}) \geq \gamma$

Algorithm 1. (Rare Sequential Patterns Builder)

                    RSPB $(L, A, \gamma, \boldsymbol{c})$;
                  end if
            end if
         end if
      end for
end for

Output : $S_m = \{(\boldsymbol{s}_m \rightarrow a_k)\}$ is a non-zero-rare activity rule set

After we hold the non-zero-rare patterns, the next stage is performing the CUS in **Algorithm 2**. In this stage, the activity label of unseen motion sensor sequences is being predicted. A simple way to predict is calculating the similarity between the generated non-zero-rare patterns with the unseen sequence by using cosine similarity. An activity label which has the highest support value is considered as the prediction result. In particular, we realize that the same cosine similarity values may be found or all the cosine similarity values are 0. These conditions indicate that there are no similar sensor types in P with the generated non-zero-rare patterns. Hence, we restrain two conditions as follows: (i) an activity label is selected randomly if the cosine similarity values are the same, and (ii) a default activity label is built in the early stage based on the maximum number of activity label in S_m To provide an activity prediction result when the cosine value is 0. The detailed procedure of CUS is presented in **Algorithm 2**.

Since this study focuses on rare pattern performance in classification, we employ a *precision* formula to evaluate our MMRSP performance. *The precision* formula is denoted by:

$$precision(\%) = \frac{tp}{tn + fp} \cdot 100\% \qquad (1)$$

where tp is a number of true positive, tn is a number of true negative and fp is a number of false positive.

Algorithm 2. (Classification Unseen Sequences)

Input: a testing set (P), and a set of non-zero-rare activity rules (S_m)

Procedure CUS (S_m, P)
a_d =defaultclass(S_m);
for each $\boldsymbol{p} \in P$ **do**
      $a_{p_i} = \underset{i \in S_m}{\operatorname{argmax}}\{\cos(\angle(\boldsymbol{p}, (\boldsymbol{s}_m \rightarrow a_m)))\}$;
      if $|a_{p_i}| > 1$ **do**
            a_{p_m} =rand(a_{p_i});
      else if $|a_{p_i}| = 0$ **do**
                  $a_{p_m} = a_d$;
      else
            count++;
            end if
      end if
end for

Output: $A_h = \{a_{p_m} | 1 \leq m \leq |P|\}$ is a set of activity labels prediction

In the next section, we will describe the dataset information and the performance evaluation of our proposed algorithm on mining non-zero-rare pattern. Furthermore, we analyze the generated non-zero-rare human activity patterns.

4. Experimental Results

We now discuss the experimental results which are started by the dataset description.

4.1 Dataset descriptions

To aim our goals, we perform the dataset from [1] on our proposed algorithm. The dataset contains recorded sensors in three apartments—their called house A, B, and C. In this study, the dataset from house A is being used. In the 'house A' dataset, it comprises 14 sensors that installed in three rooms. As the sensors are triggered, 10 activities that annotated by Bluetooth within 25 days were recorded.

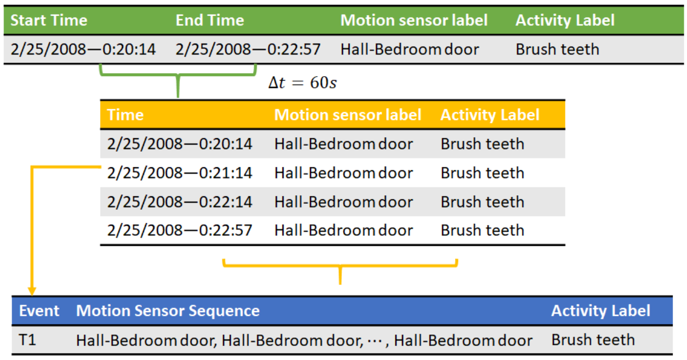
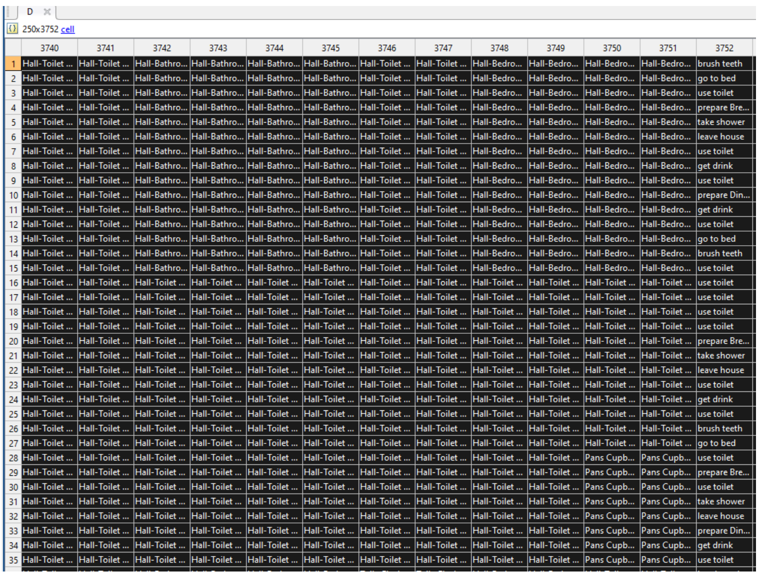


Figure 1. The transformation phase on human activity sequences

In specific, we discretize the sensory data with a different time interval $\Delta t = 60s$. As a result, we have around 42000 human activity events data. To fit in our algorithms, the dataset needs to be transformed into the form of a sequence. It can be done by taking one discretization event as one sequence with the activity label as the last item of the sequence. We provide an example of the transformation process in **Figure 1.**



D

250x3752 cell

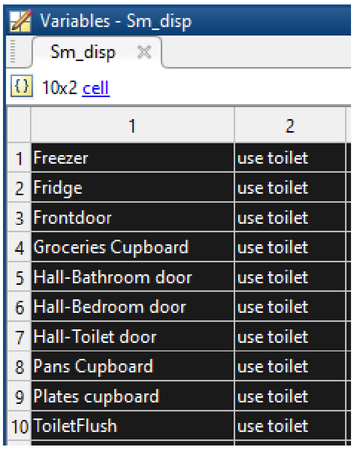
	3740	3741	3742	3743	3744	3745	3746	3747	3748	3749	3750	3751	3752
1	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	brush teeth
2	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	go to bed
3	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	use toilet
4	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	prepare Bre...
5	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	take shower
6	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	leave house
7	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	use toilet
8	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	get drink
9	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	use toilet
10	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	prepare Din...
11	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	get drink
12	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	use toilet
13	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	go to bed
14	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	brush teeth
15	Hall-Toilet ...	Hall-Toilet ...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Bathro...	Hall-Toilet ...	Hall-Toilet ...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	Hall-Bedro...	use toilet
16	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	use toilet
17	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	use toilet
18	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	use toilet
19	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	use toilet
20	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	prepare Bre...
21	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	take shower
22	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	leave house
23	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	use toilet
24	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	get drink
25	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	use toilet
26	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	brush teeth
27	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	go to bed
28	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	use toilet
29	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	prepare Bre...
30	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	use toilet
31	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	take shower
32	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	leave house
33	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	prepare Din...
34	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	get drink
35	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Hall-Toilet ...	Pans Cupb...	Pans Cupb...	use toilet

Figure 2. A human activity sequences form

Furthermore, a training set consists of 200 sequences with the maximum length is 3752 and there are 15 distinct motion sensor labels in a set of sequences S and 8 activity labels, such that `brush teeth, get drink, go to bed, leave house, prepare breakfast, prepare dinner, take a shower,` and `use toilet`. A testing set consists around 200 sequences with the maximum length is 3752 that we observe as the unseen sequences. We give an example of human activity sequences forms in **Figure 2.**

4.2 Evaluation

This study simulated on a range of γ-threshold into [0.01,1] since we found that the scale of the dataset is quite small over the number of distinct motion sensor label in S. Based on $\gamma = 0.05$, we extracted 10 non-zero-rare patterns only for `use toilet`, such as: `Freezer` → `use toilet`—motion sensor in `Freezer` is being triggered and recognized as `use toilet`, `Groceries Cupboard` → `use toilet`—motion sensor in `Groceries Cupboard` is triggered when the resident `use toilet`, etc. (see in **Figure 3**). These patterns are categorized as unusual resident activities when they still `use the toilet`. Also, we obtain 13 non-zero-rare human activity patterns only to `go to bed`. The patterns are `Dishwasher` → `go to bed`, `Plates cup board` → `go to bed`, etc.



	1	2
1	Freezer	use toilet
2	Fridge	use toilet
3	Frontdoor	use toilet
4	Groceries Cupboard	use toilet
5	Hall-Bathroom door	use toilet
6	Hall-Bedroom door	use toilet
7	Hall-Toilet door	use toilet
8	Pans Cupboard	use toilet
9	Plates cupboard	use toilet
10	ToiletFlush	use toilet

Figure 3. Non-zero-rare human activity pattern when $\gamma = 0.01$

Interestingly, we found that the number of generated non-zero-rare patterns are different for each support thresholds γ value (it is depicted in **Fig 4**). In this case, each γ value built a different particular activity that contains a different number of non-zero-rare patterns. Additionally, a support threshold γ can be represented as a particular activity event. As another viewpoint, the resident notifies that there is an unusual activity during the event and in place(s), which the sensors are triggered.

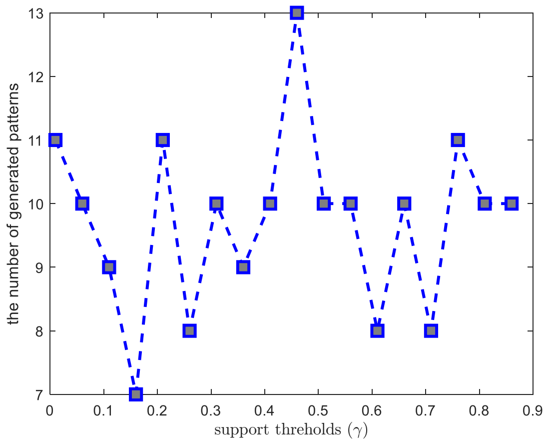


Figure 4. The number of generated non-zero-rare human activity patterns vs the support threshold values.

In addition, we test the generated non-zero-rare human activity patterns to predict the unseen sequences based on precision values. The overall precision result is 87.5%.

5. Conclusion and Future Works

As the precision result, the generated non-zero-rare human activity patterns can discover the unusual events during the residents do their activity. This can be used as an alert for the residents. Even though the MMRSP is well-performed, we still need to discuss the phenome that each support threshold give us different rare event only for a particular activity. Thus, we will obtain properties to explain the relation between support threshold and activity events in the future

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