Analyzing street crimes in Kobe city using PRISM

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Structured Abstract

Purpose

In our previous research, we proposed a security information service, called PRISM, which personalizes the incident information based on living area of individual users. The purpose of this paper is to extend PRISM in order to conduct sophisticated analysis of street crimes. The extended features enable to look back on past incident information and perform statistical analysis.

Design/methodology/approach

In order to analyze street crimes around living area in more details, we add three new features to PRISM: showing a past heat map, showing a heat map focused on specified type of incidents, and showing statistics of incidents for every type. Using these features, we visualize the dynamic transition of street crimes in a specific area and the whole region within Kobe city. We also compare different districts by statistics of street crimes.

Findings

Dynamical visualization clarifies when, where, and what kind of incident occurs frequently. Most incidents occurred along three train lines in Kobe city. Wild Boars are only witnessed in a certain region. Statistics shows that the characteristics of street crimes is completely different depend on living area.

Originality/value

Previously, many studies have been conducted to clarify factors relevant to street crimes. However, these previous studies mainly focus on interesting regions as a whole, but do not consider individual's living area. In this paper, we analyze street crimes according to user's living area using personalized security information service PRISM.

1 Introduction

Many local governments in Japan recently started providing *security information service* for residents. The service distributes information of street crimes and incidents that occurred in the region to residents using the Internet. The residents can make use of the information to avoid crimes. A typical security information service provides a list of recent incidents and a security map within a Web site. Or, it delivers the incident information by e-mail. For example, Hyogo Prefectural Police in Japan provides "Hyogo Bouhan Net" (Hyogo Prefectural Police, 2017). The service publishes incident information recognized by Hyogo prefectural Police on the Web. By registering an e-mail address, a user can also receive the information by e-mail. Similarly, Tokyo Metropolitan Police Department provides the e-mail delivery service, called "Mail Keishicho". The Department also publishes "Tokyo Crime Map" (Tokyo Metropolitan Police Department, 2017). It is a security map showing where and when every suspicious person appeared.

In these existing security information services, every incident information is uniformly delivered to all users. Various types of incidents occur every day at various locations in the region. However, user's living area varies from one person to another. Therefore, even if an incident is critical for a user, it may not be so serious for another user who is living at distant place. Thus, how the incident is severe depends on where the user is living. However, this fact is not taken into account in the existing security information services. All information of incident is distributed uniformly to all users. Hence, when much information is delivered in a day, a user may miss important information.

In our previous research, we proposed and implemented a new security information service, called *PRISM (Personalized Real-time Information with Security Map)*, which personalizes the incident information based on living area of individual users(Kagawa et al., 2017a). For every incident information provided by the existing security information services, PRISM computes severity of the incident according to the living area of a user. More specifically, based on the distance between the living area and the incident, the time elapsed from the occurrence, and the type of the incident, PRISM adds a weight to the incident, so that closer and newer incidents become more serious for the user. It then displays the weighted incidents on a heat map. Since the weight of severity varies depending on user's living area, the resultant heat map becomes a personalized and real-time security map.

The current version of PRISM visualizes the latest incident information only. It does not have features to look back on past incident information, or perform statistical analysis. Although PRISM is useful to capture the current incident status, it cannot be used for deeper analysis or visualization considering past incidents.

In order to visualize and analyze street crimes in more details, we add three new features to PRISM in this paper. The first feature is showing a past heat map. A user can display the heat map at any date in the past. By using this feature, the user can see how the incidents around the area have been changing as the time went by. The second feature is narrowing down the type of incident displayed. This allows the user to display only interesting type of incidents on the heat map. The third feature is displaying statistics of the number of occurrences for each type of incident. The user can see the number of incidents around the living area as statistical data.

Using three new features, around Kobe city in Japan, we visualize the transition of street crimes in a certain living area and the whole region. We also investigate ecology of wild boars, and compare statistics of crimes for different living areas. Using extended functionality of PRISM, the user can know when, where, and what kind of incident occurs around the registered living area.

The original version of this paper has been published as an international conference paper (Kagawa et al., 2017b). Changes made to this paper are most significantly in the addition of new data corrected in 2017. Based on the new data, we added a new section comparing street crimes between 2016 and 2017.

2 Previous Research: Security Information service PRISM

In our previous research, we have proposed PRISM (Personalized Real-time Information with Security Map), which personalizes the incident information based on living area of individual users (Kagawa et al., 2017a).

2.1 Overview of PRISM

To provide personalized incident information, PRISM exploits two key ideas. The first idea is to put a weight of *severity* on every incident. The severity is computed based on the distance to the living area, the elapsed time, and the type of the incident. The second idea is to visualize the weighted incidents on a *heat map*.

A user of PRISM first registers his/her living areas. The living areas represent places where the user often visits in the daily life, such as a house, a station, a working place, a school of user's children, or a shopping center. Every user can register multiple places as living areas.

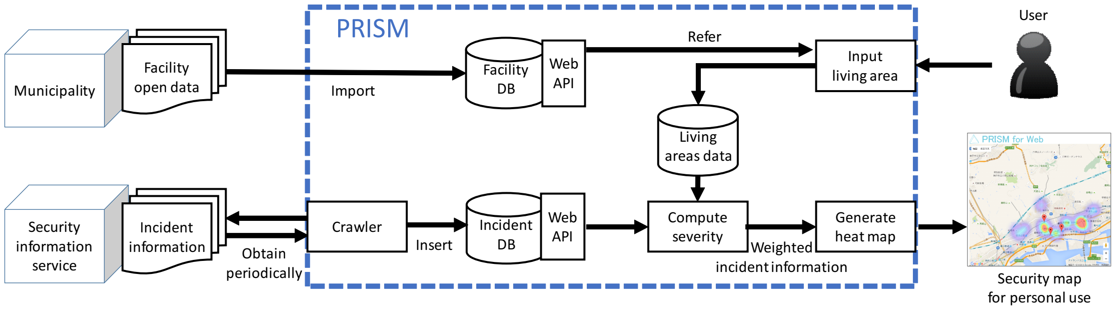

Figure 1: Architecture of PRISM

Then, for each incident information delivered, PRISM calculates the distance between the point of incident occurrence and the living area of the user. PRISM also calculates the elapsed time from date and time of occurrence to the current time. Based on the distance and the elapsed time, PRISM adjusts a weight of the default severity pre-determined for each type of incident so that closer and newer incidents are more severe. The resultant weight is the severity of the incident personalized for the user. Finally, PRISM generates a heat map based on the personalized severity, which achieves a personalized and real-time security map.

2.2 Architecture

Figure 1 shows the system architecture of PRISM. In the figure, the dotted rectangle represents the system boundary of PRISM. A *crawler*, at the bottom left of the figure, periodically obtains incident information from an existing security information service. Then, the crawler analyzes the retrieved text, extracts attributes, and inserts the attributes into an *incident DB*. A user at the top right of the figure registers his/her *living areas data*. In the registration, the user can refer to a *facility DB*, where open data about facilities provided by the local government is imported. Based on the incident DB and the living areas data, PRISM *computes the severity* of every incident. Finally, PRISM generates a heat map based on the weighted incident information, and presents the map to the user.

In the current version of PRISM, we use "Hyogo Bouhan Net" as a security information service and Kobe city facility open data (Kobe city, 2017). Using PRISM, a user can browse personalized and real-time information within Hyogo prefecture.

2.3 Severity

Severity is a degree of how the incident is serious for a user. Based on keywords contained in the incident information, PRISM first defines the default severity of incidents by the following four categories:

Alert (severity 3) The most serious incident that can threaten life of citizens. Incidents involving the following words are classified in this category: murder, robbery, shooting, assault, gun, knife, etc.

Warning (severity 2) Incidents that may cause physical damage to citizens. Incidents involving the following keywords are classified in this category: snatching, pickpocket, theft, stalking, groping, etc.

Caution (severity 1) Incidents to be paid attention, not directly linked to life or physical damage. Incidents involving the following keywords are classified in this category: scam, animal, wild boar, etc.

Notice (severity 0) Supplementary information other than street crime. Information involving the following keywords are classified in this category: arrested, resolved, notice, etc. To distinguish the supplementary information from the incident information, we set its severity to 0.

Next, PRISM weights the above default severity based on following two viewpoints:

Distance: The shorter the distance between the place of incident and user's living area is, the more serious the incident is for the user, since a new incident may happen again nearby. Thus, higher weight is given to the incident. On the other hand, the longer the distance is, the smaller the severity is.

Time: The shorter the elapsed time from the incident occurrence, the more serious it is for the user, since a new incident may happen again soon. Thus, higher weight is given to the incident. On the other hand, the longer the time is, the smaller the severity is.

Now, for an incident x and a user u, let d be the distance from living area of u to the place where x occurred. Also, let t be the elapsed time from the time when x occurred. Then, we define the severity of x for u, denoted by $severity(x, u)$, as follows:

$$severity(x, u) = \begin{cases} 0 & (severity(x) = 0) \\ 1/3 * (WD(d) + WT(t) + severity(x) * 1/3) & (\text{otherwise}) \end{cases}$$

where $WD(d)$ and $WT(t)$ are weight functions with respect to distance d and time t, respectively. $severity(x)$ represents the default severity of x (ranging over 0, 1, 2 or 3) determined by the keywords. Since $severity(x)$ takes the maximum value 3, PRISM first multiplies it by 1/3 in order to normalize the maximum value to 1. After that, $severity(x, u)$ is calculated by taking the average value of $WD(d)$, $WT(t)$, and $severity(x)$.

Currently, we use a function that maintains the weight 1.0 until d reaches 2km and decrease the weight linearly from 1.0 to 0.0 up to 4km as $WD(d)$. The threshold 4km was derived from the maximum recommended distance of commuting to schools in Japan. Similarly, $WT(t)$ maintains the weight 1.0 until t reaches 7 days and decrease the weight linearly up to 14 days. Since Hyogo Prefectural Police lists every incident information on the Web up to 2 weeks from the occurrence, we set the threshold of WT(t) to 14 days. Note, however, that the above forms of $WD(d)$ and $WT(t)$ are experimentally determined as default setting of PRISM, but are not based on crime philology or specific features of the region. PRISM has a room for a user to freely customize these functions, in case that the default setting does not fit user's sense of value for the severity.

2.4 Heat Map

PRISM displays the incident data with personalized severity on heat map. The value of $severity(x, u)$, which is the severity of incident x for user u, is between 0.0 and 1.0. PRISM creates a heat map such that the severity value is scaled into the seven colors, [purple, indigo, blue, green, yellow, orange, red]. For each incident x, PRISM puts a data point on coordinates (lat, lng) of x using a color associated with $severity(x, u)$. This generates a heat map adapted to individual living area and the current time.

Figure 2 and Figure 3 show two heat maps generated for two users A and B, where the incident information within Kobe City at a certain date is visualized. The pins in the maps indicate locations of living areas registered by the users. The colored points indicate the places where incidents occurred. In this example, user A registered Kobe Sannomiya Station and Hankyu Rokko Station as living areas. On the other hand, user B registered Hankyu Rokko Station, Shukugawa Station, and Hanshin Fukae Station. We can see that completely different heat maps are generated depending on the living area, even though the map area and the time are the same.

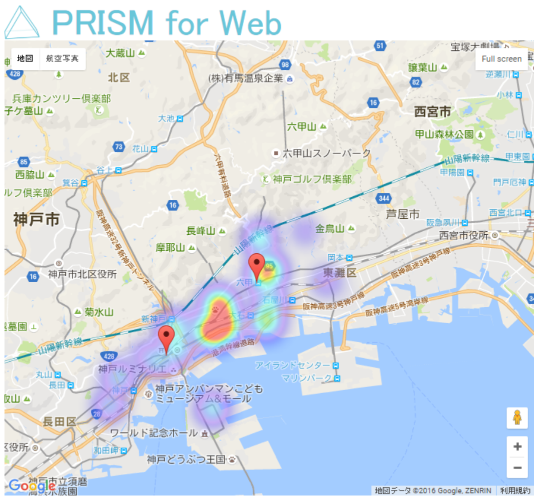

Figure 2: User A's heat map

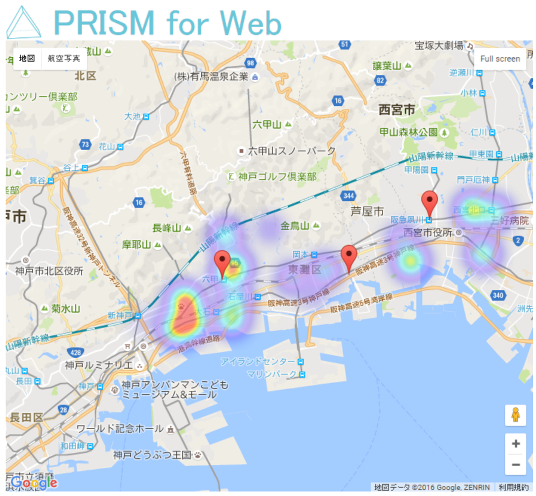

Figure 3: User B's heat map

2.5 Limitation

PRISM is good at visualizing real-time incident information. However, we consider that the current version PRISM has these three limitations.

L1: PRISM cannot look back on the past incidents. Thus, we cannot analyze where and what kind of incidents occurred in the past.

L2: Although PRISM has set the severity based on the type of incident, all types of incidents are displayed on the map. In other words, we cannot focus on specific type of incident.

L3: PRISM is a tool for visualizing the place where the incidents occurred. It does not have the feature of counting the number of incidents or performing statistical analysis.

3 Extending PRISM for Deeper Analysis

3.1 Extended Features

In order to maximize the safety and security, it is important for every citizen to grasp when, where, and what kind of incident occurs frequently around them. In this section, we propose a method to analyze street crimes in their own living area by extending PRISM.

To cope with the limitations described in Section 2.5, we add the following three features to PRISM in this paper. Using these additional features, a user can analyze temporal and statistical characteristics of incidents around his/her own living area.

F1 (Visualizing past heat map): This feature shows the heat map on any given date and time specified by the user. It allows the user to see the heat map at any point of time in the past. This feature solves L1.

F2 (Narrowing down by type of incident): This feature filters only specified type of incident on the heat map. It allows the user to focus on special types of incidents that he/she wants to analyze. This feature solves L2.

F3 (Showing incident frequency): This feature shows statistics of the number of incidents of each type as a stacked bar chart. It allows the user to analyze which type of incidents occurred and how often they did. This feature solves L3.

We will describe the details of each feature in the following subsections.

3.2 F1: Visualizing Past Heat Map

PRISM proposed in Section 2 only displays the current incident information, and cannot look back the past information. In this feature, therefore, we extend PRISM so that the user can analyze street crimes with respect to the time axis. Specifically, we allow the user to input any date and time. Regarding the given date and time as the current date and time, PRISM re-computes the severity, and re-draws the heat map as described in Section 2.4. As a result, the past heat map can be generated.

Figure 4 shows a screenshot of PRISM with the extended features. At the bottom of the map, there is a textbox for specifying the date and time The user inputs the past date and time he/she want to analyze in the text box, and presses Go button. Then, PRISM displays the heat map on the specified date and time.

On the left side of the text box, there are also buttons to look back one hour ago, or one day ago. Similarly, on the right side, there are buttons to forward the time to one hour, or one day. By using these interfaces, the user can display the heat map at any past time and analyze the distribution of street crimes.

Using feature F1 with external software taking screen shots, it is also possible to visualize the transition of incidents as an animated movie, where time-series snapshots of the heat map are linked together. Specifically, a user displays a heat map of any date in the past, and saves a screenshot with any screen capture software. Then, the user displays another heat map after one day using F1 and saves another screenshot. By repeating this d times, the screenshots of d days are obtained. Finally, by joining the saved screenshots, the user can generate the transition of the heat map during d days into an animated movie. Like this, the user can dynamically analyze where and when incidents occurred frequently.

3.3 F2: Narrowing Down by Type of Incident

In PRISM proposed in Section 2, all types of incident were displayed on the heat map. Therefore, in this feature, we extend PRISM so that street crimes can be filtered by the types of incident. Specifically, when the user designates a keyword, PRISM searches only the incidents including the keyword with API and generates heat map.

We will explain F2 using Figure 5. When the user clicks on the "Narrow down" tab at the bottom of the screen, a dropdown list for selecting keywords appears. The user selects the type of incident he/she want to analyze from the list and presses the search button. PRISM then only displays incidents which have the selected keyword on the heat map.

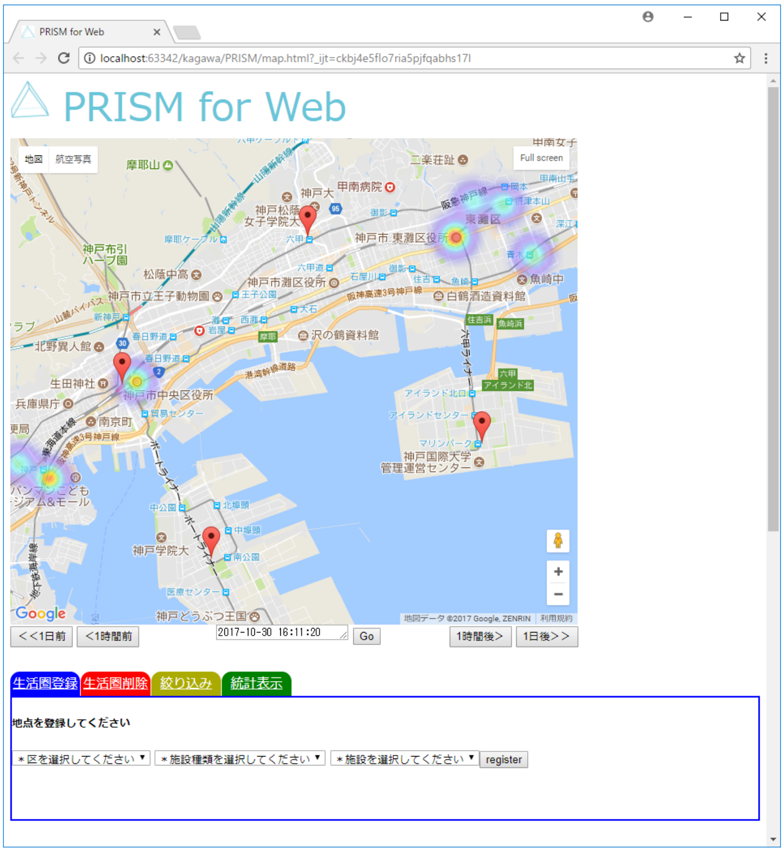

Figure 4: Feature F1: Showing heat map of past incidents

3.4 F3: Showing Incident Frequency

This feature displays the statistics of the number of incidents of each type, which we call the incident frequency. The incident frequency is represented for each registered living area, in a form of a stacked bar chart.

More specifically, for each location point p of the registered living areas, PRISM retrieves incidents that occurred within a R-kilometer radius of p and within the last D days. PRISM then counts the frequency of incidents for each incident type (see Section 3.3), and displays the statistics as a stacked bar chart. In the default setting, R is set to 2.0 km and D is set to 365 days. Thus, it is possible to take statistics of the incident frequency in the last one year within a two-kilometer radius of each point.

We explain F3 using Figure 6. When the user clicks the “Statistics” tab at the bottom of the screen, and presses the “Show statistics” button, PRISM shows stacked bar charts for all locations registered as living area. In each chart, a user can see which type of incidents occur as well as their respective occurrence rate. Thus, the user can visually analyze features of street crimes at each location point with a stacked bar chart.

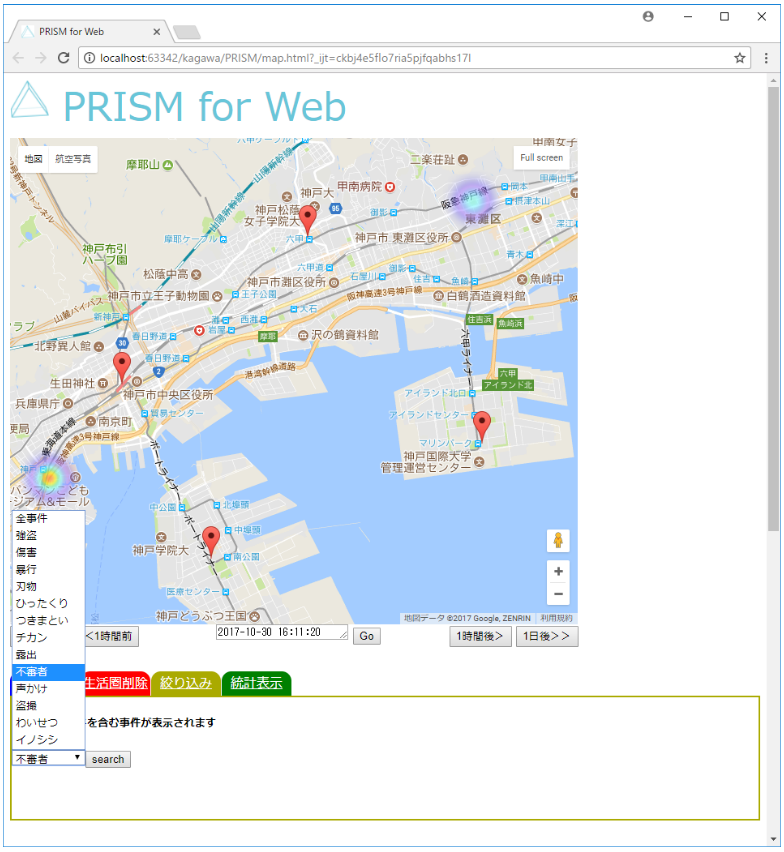

Figure 5: Feature F2: Filtering incidents by type

4 Visualizing and Analyzing Street Crimes Using PRISM

Using the extended features of PRISM, we conduct deeper analysis of street crimes within Kobe city in this section.

4.1 Transition of Street Crimes in Living Area

We analyze how the street crimes in the living areas change throughout the year. In this analysis, we adopt the Hankyu Imazu station (Nishinomiya city) and the Hankyu Rokko station (Kobe city) as personal living areas. These stations are used by the author on a daily basis. We create a video of the transition of street crimes around these stations in 2016, using F1 with the aid of "Mado Photo"[1] and "UWSC"[2].

The following steps show the concrete procedure for generating the video.

1. Display a heat map on 2016-01-01 with PRISM.

2. Capture and save a screen shot using Mado Photo.

[1] `https://www.otsoftware.net/software/madophoto.html`
[2] `https://www.vector.co.jp/soft/winnt/util/se115105.html`

Figure 6: Feature F3: Statistics of incidents for each point of living area

3. Forward the time of the heat map by one day using feature F1 of PRISM.
4. Repeat 2 and 3 by 366 times (for 366 days of the leap year). Use UWSC to automate the process.
5. Use Mado Photo again to generate an animation GIF file by combining the saved 366 screen shot.
6. Convert the GIF file into an MP4 file. The format conversion is to just increase the portability of the file, which does not affect any observable result.

We used Mado Photo and UWSC in this paper. However, a user can use any software that can save screen shots and automate the window operations.

Figure 7 shows a scene of the animation. From this, the following facts were observed:

- More incidents occurred around Imazu station than around Rokko station.
- Street crimes occur throughout the year.
- Incidents occurs various places around both stations.

Figure 7: Showing incidents around Imazu and Rokko stations (February 1, 2016)

The generated movie file can be watched at `https://youtu.be/rwaLJJG_QFA`.

In order to validate the facts observed in the animation, we examined the number of incidents around Imazu station and Rokko station. Figure 8 shows the number of incidents occurred within 2km around each station for each month in 2016. In Figure 8, it can be seen that the number of crimes around Imazu station is larger than that of Rokko station in 8 months out of 12. Similarly, as for the total number throughout the year, Imazu has more crimes than Rokko. Although the number varies over months, the street crimes keep occurring throughout the year. Thus, the observed facts can be validated by statistics.

The significant merit of generating animations is to allow a user to quickly browse the transition of street crimes within a vast area throughout a year. Although it may lack the precision compared to other numerical analysis, we consider that the visual observation is quite useful to grasp whole situation at a time.

In this experiment, we used a day as time lapse, which may skip the exact time of an incident occurrence. However, since the time weight function $WT(t)$ sustains the severity weight at least seven successive days, every incident must appear in the video. Thus, a user cannot overlook any single incident.

Depending on external software like Mado Photo and UWSC may decline user experiences. In the future, we will consider a server-side feature of generating videos, in order to make PRISM more self-contained.

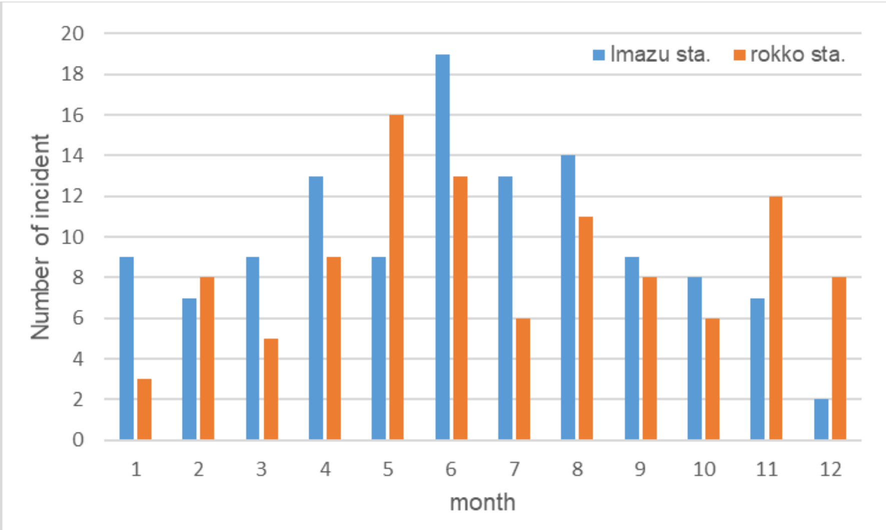

Figure 8: The number of incidents around Imazu and Rokko stations each month in 2016

4.2 Transition of Street Crimes in the Whole Region

We analyze the transition of the street crimes in the whole region of Kobe, by applying the same method described in the previous subsection.

Specifically, we place points of living areas throughout Kobe in a mesh shape. Here, we register nine points covering each ward of Kobe city, centering on Shin-Kobe station. Then, we created a movie file in the same way we described in the Section 4.1. Analyzing the animation, we investigate in which part within Kobe city incidents often occur. Figure 9 shows a snapshot of the movie. From the animation, the following facts were observed:

- Incidents occurred along three train lines (Hankyu, JR, and Hanshin) running through Kobe city.
- As it goes to the north, the number of incidents decreases.
- There are no incidents observed in mountains.

The generated movie file can be watched at `https://youtu.be/2gzVi2aJCYA`.

4.3 Ecology of Wild Boars

Since there are many mountains in Kobe city, wild boars frequently appear. Wild boars sometimes cause harm to people. Therefore, when a wild boar is observed, the location and time where the boar is found are reported to the police. Then, the witness report is delivered as an incident by Hyogo Bouhan Net. Like this, especially in Kobe City, residents need to pay attention to wild boars. Thus, for Kobe citizens, knowing where and when wild boars appear is as important as knowing street crimes. Here, we analyze the ecology of the wild boars that appeared in Kobe city in 2016, using the feature F2.

First, as similar to Figure 9 and Section 4.2, we registered nine points centered on Shin-Kobe station. Then, we specified “wild boar” as a keyword with the feature F2. As a result, only witness information of wild boars is shown in the heat map. Finally, we generated a movie file

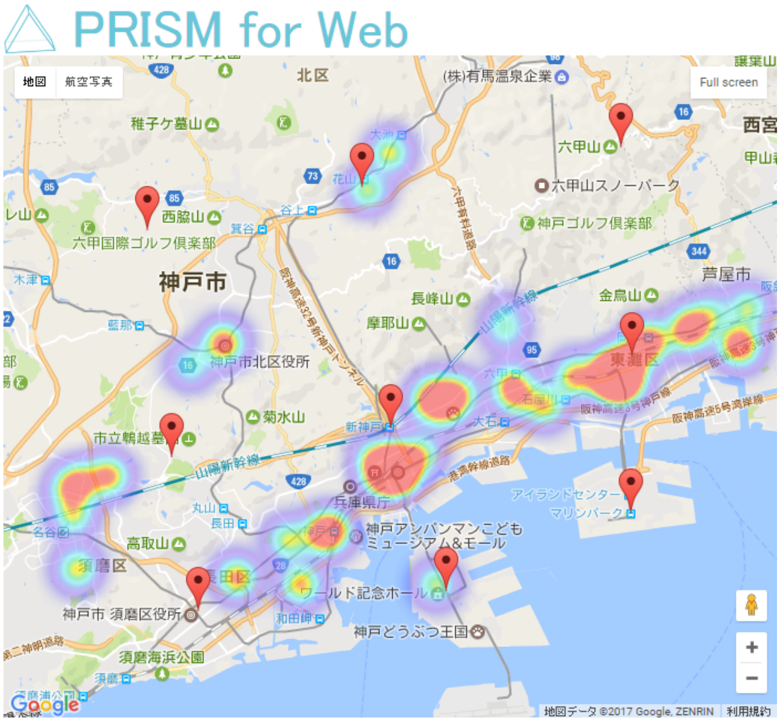

Figure 9: Showing incidents in all Kobe area (June 7, 2016)

in the same way as Section 4.1 and Section 4.2. Figure 10 shows a snapshot of the movie. From the animation, the following facts were observed:

- Most wild boars are observed within a mountain belt from Shin-Kobe station and Hankyu Okamoto station.
- Wild boars are frequently observed from June to September.
- Wild boars are not observed during the winter season.

The generated movie file can be watched at `https://youtu.be/cJSpXZlxITg`.

Another promising approach to analyze the ecology of wild boars is to exploit a smart city solution, where ambient sensors are deployed to detect wild boars. However, maintaining such sensors within a vast area is quite expensive. Therefore, in reality, the local government has to rely on the witness reports from human residents.

4.4 Comparing Statistics of Crimes

One of the biggest concerns for inhabitants is to know whether or not their living place and surroundings are actually secure. Moreover, such security information becomes a criterion for in-bound people to decide where to live. In this subsection, we analyze statistics of incidents frequency for several locations within Kobe city using the feature F3. Then, we compare the security of the locations from the viewpoint of the frequency of street crimes.

In this analysis, we compare the security around actual living houses of four users. User A's house is located in Nishinomiya city. User B's house is located in a downtown area of Nada ward,

Figure 10: Showing witness information of wild boars (June 7, 2016)

Kobe city. User C's house is located near mountains in Nada ward, Kobe city. Finally, User D's house is located in Sanda city, which is a countryside of Hyogo prefecture. We registered addresses of the four houses in PRISM, then displayed statistical information using the feature F3. We took frequency of incidents that had occurred within a two-kilometer radius in the year 2016.

Figure 11 shows four stacked bar charts generated by PRISM, each of which corresponds to statistics of a user. For clear reading, we also summarize the number of occurrences for each type of incident in Table 1.

In the neighborhood of User A's house, there are many exposures and groping. Therefore, a woman need to be careful when she walks alone. Moreover, a few serious incidents such as robbery, assault, and knife occurred. Thus, it is necessary to pay attention to these incidents. On the other hand, in the neighborhood of User B's house, there are several incidents of exposure and groping. Also, there is no incident that can threaten life of residents. However, more wild boars are observed compared to the downtown area. Thus, it is necessary to prepare for the wild boars. Fewer incidents are observed in the neighborhood of User C's house, compared to Users A and B's. However, more wild boars are witnessed, because the house is near a mountain. Thus, User C should be more careful of wild boars than User B. Since User D lives in the countryside, only six incidents are reported around his house within the year of 2016. Therefore, it can be said that User D lives in a relatively safe area compared to the other users.

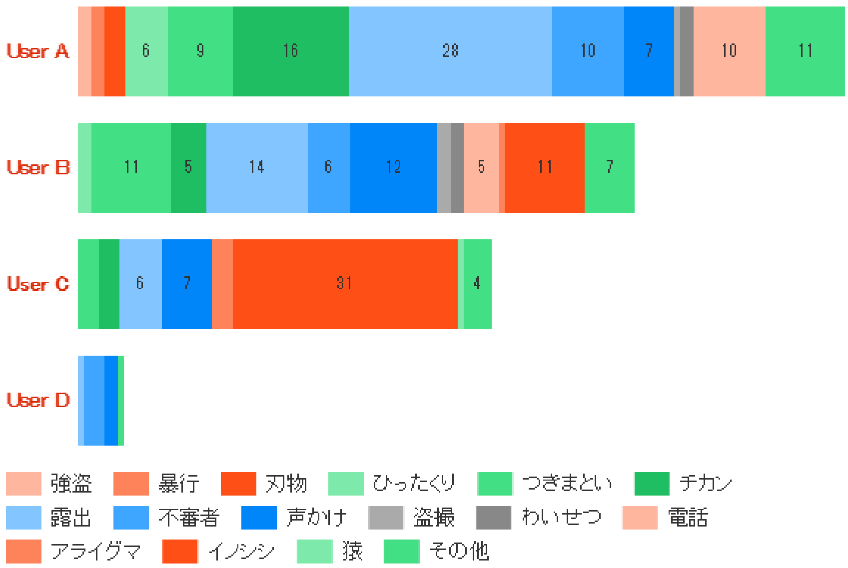

Figure 11: Showing stacked bar charts of incident statistics in 2016

4.5 Comparing Street Crimes between 2016 and 2017

In Section 4.1, 4.2, 4.3, and 4.4, we analyzed street crimes which occurred in 2016. Based on the new data, we compare street crimes between 2016 and 2017 in this subsection. Specifically, we analyze street crimes in the same way as Section 4.1 to 4.4 using the new data corrected in 2017 and compare the result with 2016.

First, we analyze the street crimes in a certain living area. We adopt the Hankyu Imazu station and the Hankyu Rokko station as personal living areas like Section 4.1. we display a series of heat maps from January 1st, 2017 to December 31st, 2017. We capture each heat map into an image file and create a movie file by joining 365 image files together. The generated movie file can be watched at `https://youtu.be/tn0_7WkcDmE`.

Next, we place points of living areas throughout Kobe in a mesh shape and analyze street crimes in the whole region and the ecology of wild boars in the same way as Section 4.2 and 4.3. The generated movie files can be watched at `https://youtu.be/hmWDx6hUFpw` and `https://youtu.be/3PvuwdNY-MQ` respectively.

From the animation, it turns out that the place where the street crime occurs does not change significantly from year to year. On the other hand, the ecology of wild boars differed. In 2016, wild boar was only witnessed in a certain area(between Shin-Kobe station and Okamoto station), but in 2017 wild boars were witnessed in the other places such as JR Kobe station and Ashiya town.

Finally, we register the same living area as that used in Section 4.4 and compare security of the locations. We took frequency of incidents that had occurred within a two-kilometer radius in the year 2017. Figure 12 shows the number of occurrences for each type of incident in 2017. In user A's living area, street crimes such as exposure decreased, however, suspicious phone calls significantly increased. In user B and C's living area with a lot of witness information of wild boars, there was no major change in the type of street crime. In the user D's living area, there were few incidents in both 2016 and 2017.

Table 1: Number of incidents every type around each house of users

	User A	User B	User C	User D
robbery	2	0	0	0
assault	2	0	0	0
knife	3	0	0	0
snatching	6	2	0	0
stalk	9	11	3	0
groping	16	5	3	0
exposure	28	14	6	0
suspicious person	10	6	0	3
act of speaking	7	12	7	2
spy photo	1	2	0	0
obscenity	2	2	0	0
phone	10	5	0	0
racoon	0	0	3	0
wild boar	0	11	31	0
monkey	0	0	1	0
others	11	7	4	1
total	107	77	58	6

We summarize the found facts comparing street crimes between 2016 and 2017.

- the place where the street crime occurs does not change significantly from year to year
- in 2017, wild boars were also witnessed in other places
- the type of incidents occurring in the living area changes depending on the year

5 Related Work

Previously, many studies have been conducted to clarify factors relevant to street crimes. Hipp and Kane focused on the relationship between population and crime(Hipp and Kane, 2017). They state that cities with more population will experience larger increases in crime. They also state that cities with increasing population will experience larger decreases in crime, regardless of the size of population. Morenoff and Sampson mentioned about the relationship between decrease of population and violent crime. They also visualized changes in the population(Morenoff and Sampson, 1997). Roncek examined how the characteristics of the area affect where crimes occur using the actual data of San Diego and Cleveland(Roncek, 1981). Stults and Hasbrouck focused on the relationship between commuting and crime rates(Stults and Hasbrouck, 2015). Kester visualized and analyzed crime patterns using Formal Concept Analysis(Kester, 2013). Their findings are interesting, however, these previous studies mainly focus on interesting regions as a whole, but do not consider individual's living area. Using the extended features of PRISM, it is possible to analyze street crimes according to an individual's living area. Tokyo Crime Map (Tokyo Metropolitan Police Department, 2017), operated by the Tokyo Metropolitan Police Department, is a security map visualizing street crimes within all cities of Tokyo. The map covers fine-grained incident information over vast area. However, Tokyo Crime Map does not consider personalization for individual users, as PRISM does so using the living area.

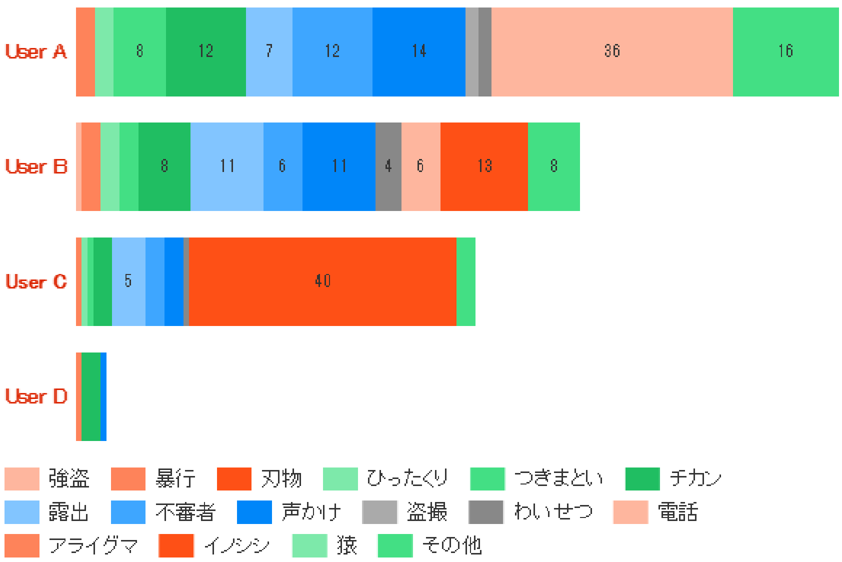

Figure 12: Showing stacked bar charts of incident statistics in 2017

Kajita et al. (Kajita and Kajita 2017) proposed a method that predicts street crimes from open data. Based on Green's Function method, their algorithm finds a causality of incidents. Their study is similar to ours in the sense that they extensively use open data of street crimes. However, their purpose is prediction, which is different from the visualization of the current or past street crimes discussed in this paper.

6 Conclusion

In this paper, we have extended a personalized security information service PRISM, in order to perform deeper analysis of street crimes and incidents within a city. Using the three new features, a PRISM user can refer to a heat map of past incidents, focus on specified type of incidents, and see the statistics of incident frequency for each type of incidents. These new features allow the user to know more deeply the characteristics of the incidents around his/her living area.

Using the extended version of PRISM, we have conducted deeper analysis of Kobe city. Transitions of street crimes within a year 2016 were analyzed for specific living area of an author as well as Kobe city. It was also interesting to see the ecology of wild boars, unveiled from incident information. Finally, we compare the security of different locations quantitatively with the incident frequency.

In our future work, we will verify the validity of the value of the severity, as well as the weight functions described in Section 2.3. In addition, although only security information in Hyogo prefecture can be browsed as it stands, we plan to implement security map in other areas, and analyze characteristics of incidents.

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