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Identifying Risk Factors for Jaywalking Using a Risk Mapping Framework

Yuichi Tokunaga*, Atsushi Yamamoto**, and Masashi Saito*

*Faculty of Graduate School of Engineering, Kanazawa Institute of Technology, Japan
**Department of Management Systems, Kanazawa Institute of Technology, Japan
{y.tokunaga, msaito}@neptune.kanazawa-it.ac.jp

Abstract -Crossing outside of a crosswalk or ignoring a traffic signal is called jaywalking. Jaywalking is a major road safety issue because even vehicles with safety features have difficulty predicting jaywalking suddenly crossing the road from the shadow of an obstacle. We hypothesize that the possibility of jaywalking is related to the road and its surrounding environment and are investigating ways to statistically estimate the risk of jaywalking from map information. To realize these ways, it is essential to identify risk factors for jaywalking, but there are a wide range of candidate risk factors, and an efficient method to identify them is needed. Therefore, we have developed a framework to generate a wide-area risk potential map from local observations and attempted to identify risk factors. The risk map framework helped streamline the procedures from factor hypothesis to verification and analysis, and we gained new insights into risk factors.

Keywords: Jaywalking, Risk map, Bayesian network.

1 INTRODUCTION

In recent years, the number of accidents involving automobiles has been on a downward trend due to the improvement of the road traffic environment, the spread of traffic safety awareness, and improvements in safety performance of vehicles. However, the number of accidents involving people versus vehicles has remained flat in recent years [1]. In particular, the number of people killed in accidents while walking continues to be the leading cause of death by condition and has begun to increase slightly. In addition, crossing violations and disregard for traffic signals account for more than 45% of the causes [2]. These dangerous behaviors of pedestrians are called "jaywalking" and countermeasures against them have become an issue in road traffic, including overseas [3]. It is assumed that elderly pedestrians jaywalk due to the overconfidence brought on by years of experience despite their declining physical ability and sensory perception. Although automobile pedestrian detection has improved over the years, the braking distance is insufficient for an emergency stop against a Jaywalker emerging from between vehicles in the oncoming lane. Prioritizing safety requires a significant reduction in speed, resulting in traffic congestion. As a result, it is difficult to avoid jaywalkers who may cross from anywhere at any time.

Common countermeasures against jaywalking include the installation of anti-crossing barriers (guardrails) and regulatory signs. Anti-crossing barriers are installed between the roadway and sidewalk to physically deter people from crossing and are considered to be an effective measure to prevent jaywalking. Regulatory signs can be installed in various locations due to their ease of installation, but they are not very effective, and neither of them is a fundamental solution to the problem.

Therefore, instead of eliminating jaywalking, we should consider foreseeing pedestrian’s jaywalking and avoiding them on the vehicle side. As mentioned above, it is difficult for vehicles to be prepared for jaywalking from all points, but by identifying points with a high probability of jaywalking, it is possible to reduce speed only there, thereby achieving both safety and avoidance of traffic congestion. Based on this idea, this paper aims to statistically determine the points of high risk of jaywalking and presents a method to identify the risk factors.

Section 2 introduces related works on jaywalking countermeasures, Section 3 describes the risk map framework we constructed to efficiently evaluate risk factors derived from these works. Section 4 uses this framework to obtain specific jaywalking risk maps, and Section 5 evaluates the results. Finally, Section 6 provides a summary and future outlook.

2 RELATED WORK

Since more than 70% of those killed in walking accidents are elderly with older than 65 years old, the behavioral psychology of road crossing for the elderly has been actively studied [2]. According to an analysis of accidents involving elderly people crossing the road by the Traffic Accident Analysis Center [4], 51% of elderly people who had accidents while crossing the road did not notice the approach of a car because they did not check for safety or check insufficiently. A typical accident scenario is shown in Fig. 1. The pedestrian first checks the path to be crossed. At that time, they see an A1's car approaching in the lane in front of them and wait for

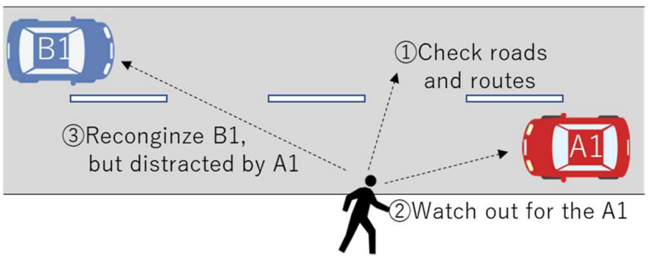

Figure 1: Mechanism of accident while crossing.

the car to pass by. They also confirm the presence of a B1's car on the opposite lane, but their attention is directed to A1. They start crossing immediately after A1 passes, continues crossing without checking left and right directions, and crosses without noticing B1 approaching from the opposite direction.

Technology to detect and avoid invisible pedestrians is being considered as the features of Advanced Driver Assistance System (ADAS) for automobiles [5]. For example, research is being conducted on technologies to recognize the movement of invisible objects from images reflected in curved mirrors and reflective objects [6][7], and to share sensing information of other vehicles, GPS information of pedestrians, and image or sensing information from infrastructure facilities through V2V, V2P, and V2I communications respectively and to detect the danger range [8]. However, all these technologies are dependent on outdoor reflective objects, sensors and cameras, and pedestrian communication devices, and thus lack versatility and do not provide fundamental solutions to the problem.

The use of risk potential maps has been proposed to reduce accidents caused by unseen hazards [9]. A risk potential map shows not only the hazards physically present in the driving path, but also the degree of danger in a space based on past cases and probability, using numerical values and colors like contour lines. For example, an intersection without a signal, which is a blind spot at a wall, has a higher danger level because of the risk of ejection. The risk map generated in this way is used to realize safe driving by presenting the driver using Head-Up-Display (HUD) and Augmented Reality (AR) or by referring in the automatic driving control to plan the low-risk routes or to control speed. Several studies and demonstrations have been conducted, but the challenge is how to narrow down the risk; if the risk map is applied to jaywalk, generalized to roads without pedestrian crossings, the jaywalk risk is high, and cars are always forced to drive at low speeds. On the other hand, if only points where jaywalking has occurred in the past are considered high risk, accidents caused by jaywalking at other points cannot be prevented. It is necessary to narrow down the risk value with more accurate information.

On the other hand, there have been many studies on pedestrian crossing behavior from the viewpoint of road design in the field of civil engineering planning [10][11]. Hamamoto et al. studied pedestrian behavior at a national road intersection leading to a station connection [12] and explained that pedestrians want to take the shortest route possible, and if there is a possible crossing on the route, they will cross even if it is outside the pedestrian crossing area. The study notes that jaywalking is more likely to occur at locations where crossing cannot be physically deterred, such as street intersections, entrances to roadside facilities, and openings in anti-crossing barriers. Takehira also studied the relationship between roadway facilities and jaywalking on several roads in densely populated urban areas [13]. Unlike national roads, anti-crossing barriers on urban streets are often characterized by disconnection at the approaches to stores and parking. In all the study locations observed, more than 90% of the disorderly crossings occurred at locations where there were openings at both the start and end points.

These studies indicate that the likelihood of jaywalking occurring depends on the condition of the road environment surrounding the pedestrian, such as intersections and anti-crossing barriers. Studies have been published that focus on this point and incorporate it into risk assessment for pedestrians. Wang et al. propose a risk assessment method for pedestrians who jump from the shadow of a car onto the roadway for automated driving on public roads [14]. They used Dynamic Bayesian Networks (DBN) to determine the probability that a pedestrian exists in the shadow of a car and that the pedestrian will enter the roadway. They hypothesized that pedestrian behavior of entering the roadway was due to the road and traffic environment and attempted to identify the risk factors by observing crossing behavior. Observations showed a link between the road environment and disorderly crossing, but the proposed risk assessment method was only validated in a computer simulation and not evaluated in a real environment.

Thus, it is shown that the potential risk of jaywalking may be inferred from the road environment, and anti-crossing barriers are an important clue in estimating jaywalk risk. On the other hand, many community streets and suburban roads are not equipped with anti-crossing barriers, and the presence or absence of such barriers alone cannot narrow down the potential risk area of jaywalking. It is essential to discover environmental impact factors other than anti-crossing barriers for risk mapping that aims at both safety and traffic efficiency.

3 RISKMAP FRAMEWORK

3.1 Target Setting

Related works have shown that the opening of an anti-crossing fence affects the probability of jaywalking occurring. Other road traffic environment influences have also been suggested. So, as shown in Fig. 2, if we create a model to estimate the probability of jaywalking based on these road environment characteristics in a certain limited area and expand it to the whole country using map information and this estimation model, we can create a general jaywalking risk

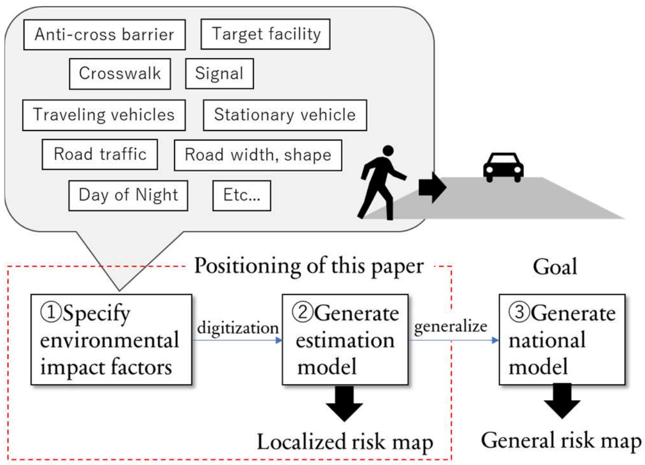

Figure 2: Approach to create a jaywalking risk map.

map. However, to narrow down the risk area, it is necessary to specifically identify features other than anti-crossing barriers.

Therefore, we formulate a hypothesis based on use cases. Facilities where people gather, such as train stations and schools, are often located on main streets, and pedestrians targeting the facility flow into the main street from side streets near the facility, bypassing nearby pedestrian crossings to follow them to the facility. If there are no crosswalks nearby, the behavioral psychology of choosing the shortest route is at work, and pedestrians are more likely to cross at the point where they exit the side street onto the main street. Based on this use case, it is highly likely that the mutual location of the facility where people congregate, the influx of side streets in the vicinity, and the crosswalks affect the potential risk probability of jaywalking. The goal of this study is to substantiate this hypothesis.

To achieve this goal, we will generate a jaywalking estimation model based on the location of facilities and other features and crosswalks and evaluate whether the risk map derived from the model is valid outside of the observation points.

3.2 Framework Construction

Creating a jaywalking estimation model requires the development of factors such as facility type and feature extraction, as well as observational data. On the other hand, whether an appropriate risk map can be obtained depends on the hypotheses based on use cases, and there is no guarantee that the results will be worth the effort of creating the model. Therefore, the initial stage is to generate a model from a minimal dataset to prove the hypothesis, the process of expanding the missing variables and data is repeated. In this iterative process, as shown in Fig. 3, the collection of observation data, generation of data sets, model generation, and risk visualization can be automated, and therefore, these can be built as a framework to improve efficiency.

An overview of the framework is shown in Fig. 4. First, location information of features in the road environment that induce jaywalking, such as facilities and pedestrian crossings, are automatically obtained using open data. Next, location dataset is created, and an estimation model is generated. Utilizing the created estimation model, the probability of occurrence of jaywalk is estimated. Finally, a heat map is superimposed on the map using the occurrence probability as the risk value to create a jaywalking risk map. Each of these functions is described below.

3.2.1 Extraction of Location Information on the Road Environment

Google Maps is used to automatically acquire location information of features on the road environment that trigger jaywalk. Facilities such as stations and schools are listed by the search function and their latitude and longitude information is obtained. On the other hand, pedestrian crossings cannot be extracted by the search function. As a method to address this problem, a study has been reported that analyzes aerial photo images to detect pedestrian crossings

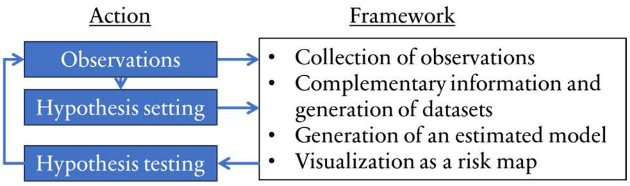

Figure 3: Positioning of the framework.

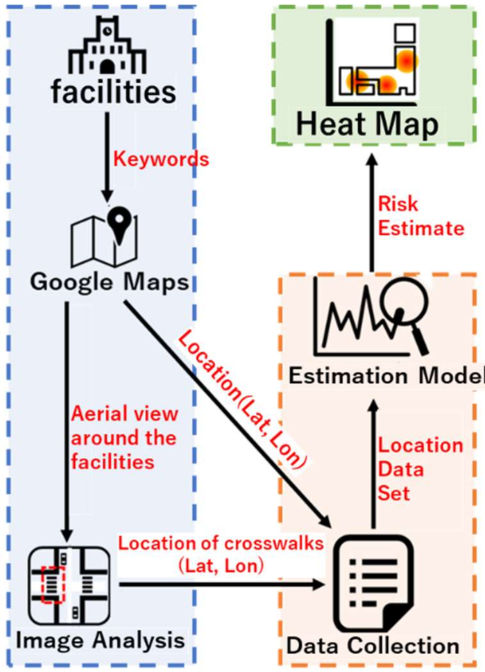

Figure 4: Framework overview.

[15][16], and we will use the same method. The method of extracting crosswalks is explained in 4.1.2.

3.2.2 Generating an Estimation Model

Next, a location dataset is created from the calculated latitude and longitude information. The presence or absence of jaywalking is observed in advance from visual surveys, and the data is created by calculating the distance and direction for each latitude and longitude of the observation location. The created data is compiled as location data, and an estimation model is created using a Bayesian network.

Bayesian network is a probabilistic inference model that shows multiple causal relationships in a weighted graph structure (network) and indicates each causal relationship by probability [17]. Even when the full picture of causal relationships is not known, the estimation accuracy can be improved by accumulating findings obtained through observation as partial causal relationships. We believe that this is the best method for this project to clarify the causal relationship of the jaywalking outbreak through repeated hypotheses and observations.

Bayesian network can be expressed by the following equation:

$$P(x_1, \dots, x_N) = \prod_{i=1}^{N} P\big(x_i \big| parent(x_i)\big) \quad (1)$$

where x_i denotes each event and $parent(x_i)$ denotes the upper event in the relationship. The probability of occurrence of a given combination of events is expressed as the product of the conditional probabilities of each causal relationship.

From the hypotheses set up in this paper, x_i indicates the relationship between the location of the facility at the observation point, the road structure, and the location of the pedestrian crossing. The model is generated by data on the jaywalking situation at each observation point, analyzing the dependencies between each causal event and determining the conditional probability of each relationship.

Bayesian estimation was used to create the estimation model. Details of the location dataset and estimation model are described in 4.2.2 and 4.2.3.

3.2.3 Generating a Jaywalking Risk Map

Finally, a jaywalking risk map is created by overlaying a heat map on a map with the probability of jaywalking as the risk value. The colors displayed on the heatmap should be separated according to the risk values so that the information can be obtained visually.

4 APPLYING THE FRAMEWORK

The constructed framework is used to generate risk maps based on the risk factors hypothesized in the use cases in Section 3.1. Specifically, the latitude and longitude of structures are automatically obtained from Google Map searches to create a dataset of the location relationship between gathering places and pedestrians, and crosswalks are detected and located from aerial images to create a dataset of the location relationship between pedestrians and crosswalks. Based on these location relationships and the observed information on the availability of jaywalking, a Bayesian estimation model is created, and a jaywalking risk map is generated. This section describes the acquisition of crosswalk location information, creation of the Bayesian estimation model, and generation of the risk map.

4.1 Extracting Crosswalk Locations

4.1.1 Image Collection

Using the location data (latitude and longitude) of the facility retrieved by Google Maps, aerial images centered on the facility (or its center of gravity in the case of multiple facilities) are collected from the Google Maps Platform (hereinafter referred to as "GMP"). GMP outputs a 70-meter square aerial image by specifying the location data of the center of the image to be acquired. Assuming a 1 km square risk map, the location data sets of 15 x 15 = 225 images must be specified to GMP. To minimize gaps and overlaps at image boundaries, the location data of the center point of each image was determined using the Vincent method from the latitude and longitude of the center point of the target area, and the distance and direction of each image. These data sets were input into GMP to obtain the images.

4.1.2 Extraction of Crosswalks

Although several methods have been proposed for extracting pedestrian crossings from aerial images, we apply YOLO v5, which is widely used for general object detection applications. We trained on 300 crosswalk images extracted from aerial photographs and obtained a high detection accuracy with an F value of 0.95 by setting confidence>= 0.8.

Using the acquired crosswalk coordinate information and the latitude and longitude information of the images, the latitude and longitude of the crosswalk are calculated YOLO outputs the coordinate information of the bounding box of the detected object. Since the latitude and longitude information of the center of the original image is known, the latitude and longitude information of the center of the bounding box was calculated from this information, and this was used as the location of the crosswalk.

4.2 Creating a Bayesian Network Model

4.2.1 Collection of Training Data

To obtain the training data, a visual survey of jaywalking was conducted. The survey covered an area of 80 meters from north to south and 800 meters from east to west, centered on the main road that passes in front of the main gate of the university, and observed jaywalking for 20 minutes starting at 8:20, when students are concentrated at school. Six surveyors were assigned to the survey area to record the starting point of jaywalking and the crossing direction. In order to investigate the usual situation, the surveyors were students, and they pretended to meet up with others so that they would not be recognized as being in the middle of a survey, and no photographs were taken. Although the percentage of pedestrians killed in accidents while walking is higher among the elderly, we observed jaywalking among all age groups of pedestrians, as jaywalking is done regardless of age. The overview of the study area is shown in Fig. 5 and the time trends of observed jaywalking are shown in Fig. 6. Red boxes in Fig. 5 indicate locations where jaywalks were observed, and black boxes indicate locations where a particularly large number of jaywalks were observed. Many jaywalkers were observed at the intersection of side streets to the main street, and many pedestrians were observed jaywalking not only to and from the university but also to and from the supermarket.

4.2.2 Creation of Dataset

The dataset consists of five study area divided into a 1-meter square mesh, and four items, distance and direction to the nearest facility (in this case, a university), distance and direction to the nearest pedestrian crossing, were calculated based on the location information of facilities and pedestrian crossing groups obtained by the methods described in Sections 3.2.1 and 4.1. Note that although road structure is also a candidate for jaywalking risk factor in the hypotheses of section 3.1, it was excluded from the item because the criteria for categorization had not been clarified. This is one of the issues to be addressed in the future.

Figure 5: Observation points of jaywalking.

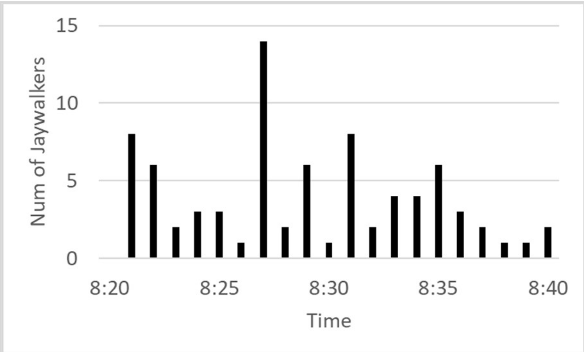

Figure 6: Trends in occurrence of Jaywalking.

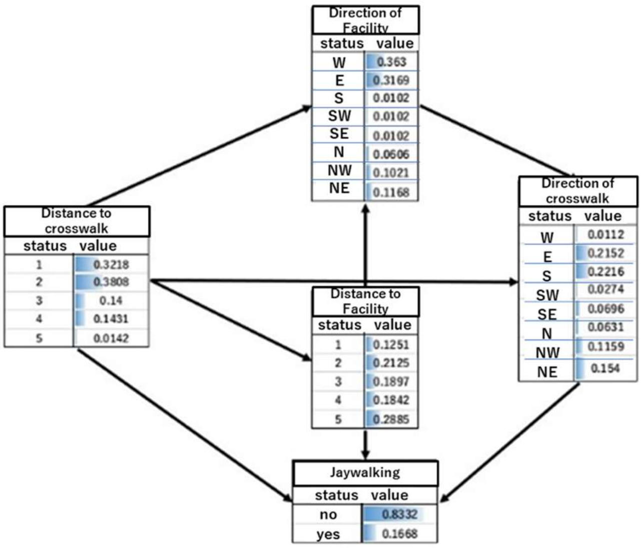

Figure7: Created Bayesian network.

The results of the visual survey are added here: the number of observations is added to the mesh corresponding to the starting point of the jaywalking. If a mesh was not observed during the 20 minutes of the survey period, it is set to 0. If multiple jaywalking was observed, the number of times it was observed is recorded. As described above, the survey results for an area of 80 meters from north to south and 800 meters from east to west are divided into 80 meshes x 800 meshes = 68,000 records, and values for 5 items in each record are generated.

Figure 8: Jaywalking risk map.

4.2.3 Estimation Model Generation

BayoLinkS [18], software for building Bayesian network, was used for model generation. This software can learn structures from data, extract dependencies (Bayesian networks), and generate estimation models. Since the data needed to be discretized, the distances in the dataset were equally divided every 50 meters, and the directions were labeled in eight levels: east, west, south, north, and south. The number of divisions for discretization has a significant impact on model performance, so the appropriate number of divisions is an issue to be considered in the future.

The Bayesian network constructed by structural learning is shown in Fig. 7. The solid line shows the dependencies, and the table below the items shows the probability of occurrence of each state relative to jaywalking probability. In the current study, the distance to the facility and the crosswalk and the direction of the crosswalk are directly causally related to the occurrence of jaywalking, while the direction of the facility is causally related to the direction of the crosswalk. This is considered to be a result of the influence of the learned terrain and is a challenge when generalization, i.e., when the model is used to estimate other areas.

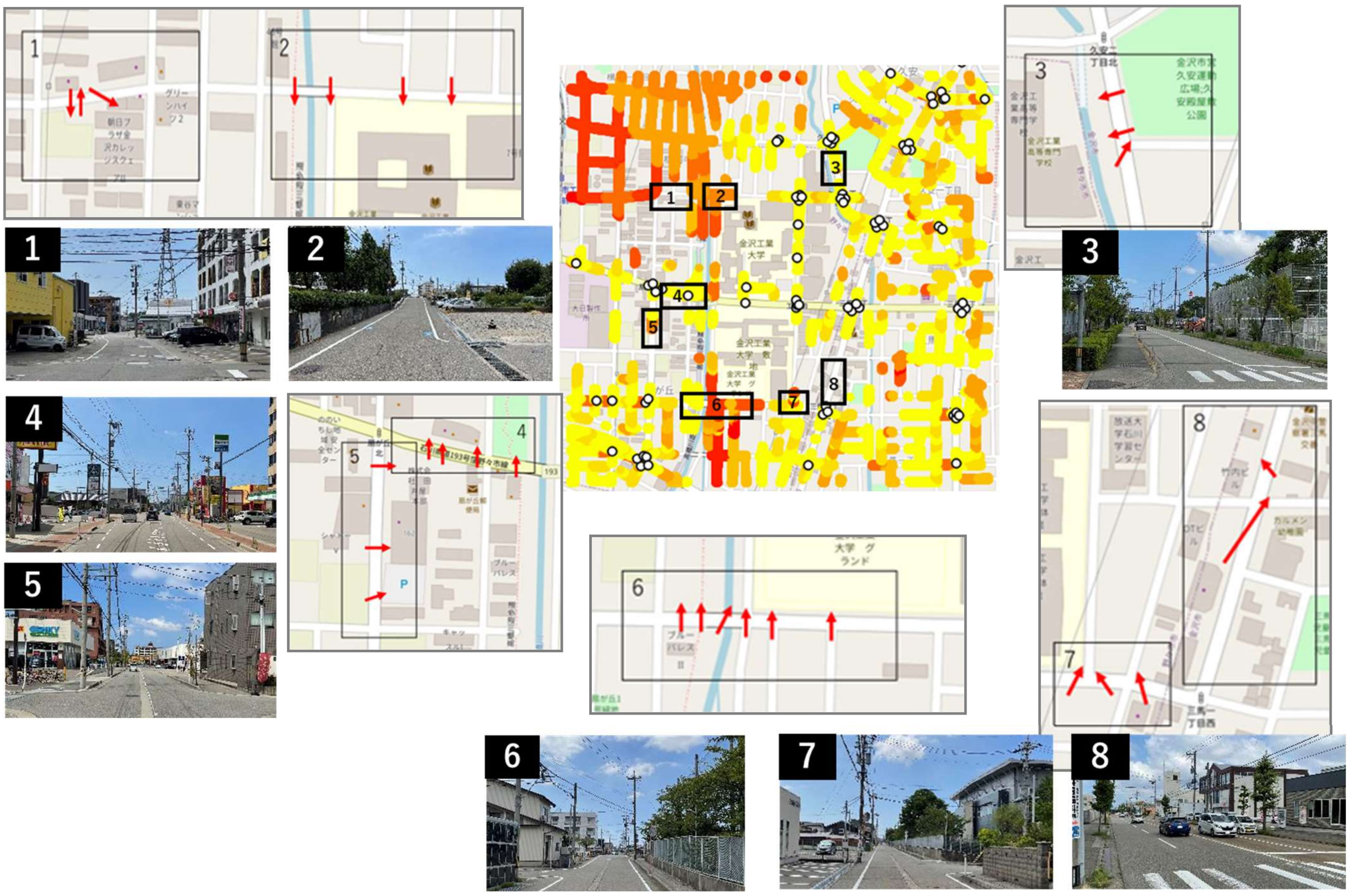

Figure 9: Observation results.

4.3 Risk Map Generation

The risk maps are generated in QGIS, using the estimation model generated by BayoLinkS to obtain the probability of jaywalking occurrence for each mesh location, which is then converted into a heat map. Since we want to show a risk map for a road, we obtain road information from OpenStreetMap and display the probability of occurrence only for the mesh location that overlaps the road. The created risk map is shown in Fig. 8. The circled dots represent pedestrian crossings.

The green boxes indicate visual survey locations, i.e., areas of correct data. The upper left corner of the map indicates a high-risk area. This area is considered high-risk because it is a residential area and there are no pedestrian crossings. On the other hand, there are no areas near pedestrian crossings that are indicated as high risk, indicating that the distance from the pedestrian crossing has a significant impact.

5 EVALUATION

5.1 Evaluation Method

To evaluate the hypothesis using the created signal neglect risk map, a visual survey of jaywalking will be conducted again. Eight sites will be randomly selected from a wider area than during the survey to obtain training data, and jaywalking will be observed for 20 minutes. We will evaluate the consistency between the frequency of jaywalking indicated by the results and the hazard level of the risk map. The location of each point is shown in Fig. 9.

5.2 Evaluation Results

Regardless of the results of the risk estimation, jaywalking was observed at all points and the hypothesized estimation results were determined to be unreliable. To clarify the problem with the hypothesis, the status of jaywalking at each point was analyzed.

Point 1: High risk determination with no pedestrian crossing in the vicinity. A convenience store fronting a two-lane road with a parking lot and café in front of it. jaywalk was identified between the convenience store, parking lot and cafe. The destination was hypothesized to be the university because the observation time coincided with the students' commute to school; however, considering that many students stop at the convenience store, the stopping establishment should be included in the destination.

Point 2: The risk map shows a high-risk level due to the lack of pedestrian crossings in the vicinity. Visual surveys also identified jaywalking on all streets, and the risk level is correctly estimated.

Point 3: Crosswalks are located approximately 50 m apart, and the risk map estimates the risk level to be low; however, a signal failure in the direction of the entrance to the sports field was observed at the midpoint of both crosswalks. As with point 1, lack of destination setting is considered to be the cause of the discrepancy.

Point 4: Low risk determination with crosswalks approximately 20 m apart, with a convenience store and park fronting the two-lane road. Jaywalking was observed despite the proximity of the pedestrian crossing. The convenience store to stop at is on the opposite side of the road, and the straight road with good visibility suggests that the driver is crossing the street without using a pedestrian crossing. In addition to the additional destination, the factor of road visibility was found to be necessary.

Point 5: Intermediate risk determination near a signalized intersection. There is a bookstore facing a two-lane road with good visibility. Jaywalk was observed avoiding the signalized tail crossing. The situation is considered similar to the situation in point 4.

Point 6: A medium to high-risk determination on a residential street with no crosswalks. As in point 2, jaywalking across a two-lane road from each residential street is identified and the risk is correctly estimated.

Point 7: Medium risk determination near a signalized intersection. Signal failure to use crosswalk was observed on the route from the convenience store to the main gate of the University. jaywalking direction is consistent with the direction toward the University.

Point 8: A four-lane road with signalized crosswalks at approximately 100 m intervals. Low risk determination. Jaywalk was confirmed to be heading toward a family restaurant in the middle of the road. The situation is considered similar to that of Point 1.

As described above, no correlation is obtained between the risk estimate of each point and the frequency of jaywalking, and it is not possible to substantiate the hypothesis that the mutual location of the facilities where people gather, the influx of side streets around them, and the crosswalks affect the risk value of jaywalks. However, for Points 1, 3, 4, 5, 7, and 8, jaywalking targeting stores and facilities where people often stop on their way to school is confirmed, and by registering these as additional facilities that contribute to jaywalks and having the risk estimated based on the location relationship with the nearest facility, an improvement in the accuracy of the risk map This function is expected to improve the accuracy of the risk map. This functionality is an improvement to the framework and will be considered an issue to be addressed in the future.

Furthermore, for points 4 and 5, visibility is thought to induce jaywalking, indicating the need for a new factor that expresses visibility in terms of road width and straightness. For points 2 and 6, the road structure needs to be added as a factor, as the shortest route to the university is a residential street, which is blocked by a two-lane road. The developed framework does not yet support road features, but we believe it is possible to extract them from aerial photographs in the same way as pedestrian crossings, and this is another area for improvement.

6 CONCLUSION

This study attempted to identify risk factors for jaywalking in order to visualize the probability of jaywalking as a potential risk. Based on the results of related research, such as the behavioral psychology of people crossing a road and the effects of facilities that obstruct crossing, such as anti-crossing fences, it was found that the road and its surrounding environment have an influence on the occurrence of jaywalking. Therefore, we hypothesized that the mutual location of facilities where people gather, side roads and crosswalks that flow into the surrounding area affect the occurrence of jaywalking, and constructed an environment that can be used as a framework to materialize this hypothesis. Keyword facility locations from Google Maps and crosswalk locations from aerial photo image analysis were extracted to create a dataset along with Jaywalking observation data. Using this data, a Bayesian network risk estimation model was created to display the risk of jaywalking on the road in a QGIS heat map. Based on this, it is possible to efficiently evaluate whether the hypothesized risk factors can be generalized by re-observation.

The model was generated based on observations of jaywalking in the vicinity of university facilities, and this model was applied to the outer perimeter of the university to evaluate the risk map and actual conditions through observation, but the results were not as expected. After analyzing the observation results, it was found that the hypothetical problem requires the presence of multiple types of facilities. It was also found that the road structure, which has not been implemented, is likely to be an important risk factor.

Although the objective of this study to identify risk factors for jaywalking has not been achieved, the framework we have developed allows us to efficiently move on to the next hypothesis. In the future, we aim to improve the accuracy of jaywalking risk estimation by identifying risk factors through repeated PDCA cycles for the hypotheses.

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Yuichi Tokunaga received a ph.D. degree in science and engineering from Ritsumeikan University in 2009. He joined Mitsubishi Electric Corporation in 1990 and engaged in R&D of the high-reliability computer, wireless sensor network, the algorithms of time-synchronization and positioning, the network protocol for industrial applications, and data analytics for CBM (Condition Based Maintenance). He has been a professor at Kanazawa Institute of Technology since 2019. He is a member of the ITS steering committee of IPSJ and a member of IEEE and ISCIE.

Atsushi Yamamoto graduated in March 2023 from the Department of Management Systems, College of Informatics and Human Communication, Kanazawa Institute of Technology.

Masashi Saito received B.E degree from Tokyo Institute of Technology in 1983, M. E. degree from Cornell University in 1992 and Ph.D. degree from Osaka University in 2006. In 1983, he joined Mitsubishi Electric Corporation and has developed engineering workstations, Internet TVs, cellular phones, car navigation systems especially for operating system extension, Internet services and distributed processing. In 2006, he moved to Mitsubishi Electric Research Laboratories as a senior principal technical staff. Since 2015, he has been a professor at College of Informatics and Human Communication, Kanazawa Institute of Technology. His current research interests include ITS, distributed systems, smart communities and smart social systems. He is a member of IEEE and IPSJ.