SPWID 2017

The Third International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems

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SPWID 2017 Editors

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SPWID 2017

Forward

The Third International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems (SPWID 2017), held between June 25-29, 2017 in Venice, Italy, was an inaugural event bridging the concepts and the communities dealing with specialized implantable, wearable, near-body or mobile devices, including artificial organs, body-driven technologies, and assistive services.

Mobile communications played by the proliferation of smartphones and practical aspects of designing such systems and developing specific applications raise particular challenges for a successful acceptance and deployment.

The conference had the following tracks:

- Spatio-temporal Analysis for Smart City

We take here the opportunity to warmly thank all the members of the SPWID 2017 technical program committee, as well as all the reviewers. The creation of such a high quality conference program would not have been possible without their involvement. We also kindly thank all the authors that dedicated much of their time and effort to contribute to SPWID 2017. We truly believe that, thanks to all these efforts, the final conference program consisted of top quality contributions.

We also gratefully thank the members of the SPWID 2017 organizing committee for their help in handling the logistics and for their work that made this professional meeting a success.

We hope that SPWID 2017 was a successful international forum for the exchange of ideas and results between academia and industry and to promote further progress in the field of smart portable, wearable, implantable and disability-oriented devices and systems. We also hope that Venice, Italy provided a pleasant environment during the conference and everyone saved some time to enjoy the unique charm of the city.

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Detecting Garbage Collection Duration Using Motion Sensors Mounted on Garbage Trucks Toward Smart Waste Management

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***Abstract*—Solid waste collection is one of the fundamental services provided by local governments in support of our daily lives. In this paper, we describe a basic framework for estimating the amounts of solid waste and propose a method for detecting the time required for garbage collection with a view to realizing smart waste management. The proposed method recognizes garbage collection duration by using motion sensors mounted on a garbage truck. We also report a preliminary evaluation of the proposed method using actual motion sensor data.**

***Keywords*–Smart city; Activity recognition;**

I. Introduction

Solid waste collection is one of the fundamental services provided by local governments in support of our daily lives. Efficient waste management is important if we are to sustain stable waste collection service in the future. The optimization of waste collection operations and domestic waste reduction are key factors related to efficient waste management. At the same time, we are investigating smart city sensing using car-mounted sensors. Smart waste management using garbage trucks equipped with sensors could provide a powerful solution. In this paper, we propose a method for detecting the time required for garbage collection with a view to realizing smart waste management.

In conventional waste management, the amount of solid waste for a given region is summarized by weighting the waste delivered by garbage trucks assigned to the region to incineration plants. In fact, one truck collects solid waste in multiple separated areas to allow workload balancing, and therefore the summarized result includes some degree of error and waste collection operations are planned based on human intuition.

We propose a method for estimating regional amounts of solid waste based on the garbage collection duration in each area and the waste weight measured at incineration plants. The garbage collection duration is estimated from the vibration of the garbage truck when it scoops up the garbage with a rotating plate. We mounted motion sensors on garbage trucks and measured the changes in vibration. This paper reports a preliminary evaluation of our estimation of garbage collection duration and discusses the feasibility of the proposed method.

Determining the estimated amounts of regional amounts of solid waste enable us to realize the following applications.

- Support when planning future solid waste collection: We can obtain the long-term fluctuation and regional seasonal variations in the amount of solid waste by measuring the amounts in small areas such as those covered by a residents' association. This information will also enable us to estimate future solid-waste amounts in detail thus allowing waste management planning.
- Feedback garbage amounts to citizens:
  Most residents know neither the amount of garbage that they produce nor the total amount of garbage in their area. If a resident knows that he produces more than the average amount of garbage, he will try to reduce it. Moreover, if a resident knows that the total amount of garbage produced by his residents' association is less than the average, he may try to persuade his neighbors not to exceed the average. In this way, regional feedback regarding the amount of solid waste will promote its reduction.

This paper describes a method for detecting the time taken by a garbage truck during garbage collection and a method for estimating the amount of solid waste that is collected. We also report a preliminary evaluation of the collection duration detection method using actual motion sensor data.

II. Related work

Activity recognition research using motion sensors started with human activity recognition [2] and studies are under way with a variety of targets such as animals, buildings, cars [6]. Moreover, most recent smartphones are equipped with motion sensors. We can easily develop such activity recognition systems for use in various fields.

Recently, a road surface quality monitoring system using a mobile device was proposed [7]. This system allows us to monitor road surface quality without the need for a dedicated car. Although we use dedicated sensor nodes for field trials, we consider that we can detect the time taken for garbage collection using a smartphone equipped with a motion sensor.

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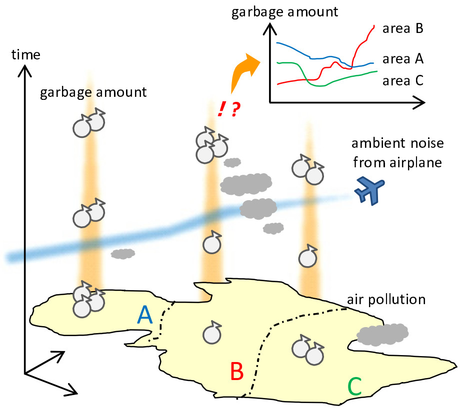


Figure 1. Spatio-temporal event detection using car mounted sensors

In the future, it is possible that we will be able to monitor road surface quality and measure regional solid-waste amounts simultaneously using motion sensors mounted on the garbage trucks that travel around cities every day.

There is another type of smart waste management in which smart sensors are attached to garbage carts [3]. We can monitor the number of garbage carts remotely, and the best garbage collection route is provided by the service providers. However, this approach is not available for some types of garbage collection system such as where residents place their garbage in bags in front of their house and the bags are regularly collected by trucks.

III. Sensorized Garbage Truck

We are investigating city event detection technology using environmental data collected via car-mounted sensors. Car-mounted sensors provide significantly more detailed data both in space and time than fixed monitoring stations. Figure 1 shows an image of spatio-temporal event detection. Such fine-grained environmental data help us to detect spatio-temporal city events in more depth, for example the emergence of air pollution hot spots, the generation of ambient noise, and sudden increases in residential solid waste.

We have installed dozens of car-mounted sensors on garbage trucks that travel daily around Fujisawa city, Kanagawa, Japan [1], [5]. Figure 2 is a picture of a sensorized garbage truck. The truck is equipped with four microphones, a GPS receiver, a motion sensor, and a sensor node to manage these sensors. We also installed various types of sensors such as NO_2, CO, $PM_{2.5}$, temperature, humidity, UV sensors on other garbage trucks. Sensor data measured by these sensorized garbage trucks are sent to a data server via a mobile Internet connection service.

IV. Residential Solid Waste Collection in Japan

This section describes residential solid waste collection in Japan in detail. Garbage bags are put out in front of houses facing the road or at collection sites and are regularly collected by garbage trucks. Solid waste is separated into several types such as combustible waste, incombustible waste, glass bottles, recyclable plastic, and paper. Each type of waste is collected on a designated day of the week.

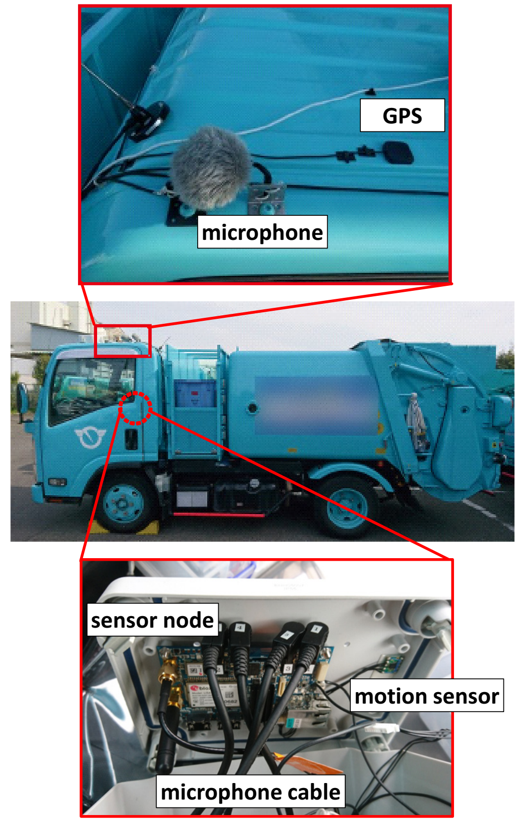


Figure 2. Sensorized garbage truck

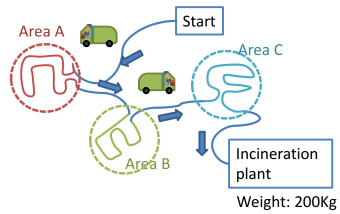
Regarding residential solid waste collection, a garbage collector drives a garbage truck to the assigned area. He stops the truck at each collection site or in front of a house and loads garbage bags into the truck by hand. Actual examples of garbage collection in Japan are shown in [8]. When the opening at the back of the truck is full, the garbage collector starts the rolling plate and the garbage bags are packed into the container. Before the container of the truck is full, he drives to an incineration plant or a recycle plant. The weight of the collected solid waste is measured at the plant.

In Fujisawa city, the site of our experimental facility, the garbage collector plans a detailed garbage collection route at his discretion, and he also decides when to visit the incineration plant depending on traffic condition, road construction schedule, and the amount of garbage. Sometime a garbage collector is asked to collect forgotten garbage from another garbage truck temporarily. Thus, we cannot obtain the regional solid-waste amount in detail using only the measured weight of solid waste in incineration plant.

V. Solid Waste Weight Estimation Scheme

We assume that the operating duration of the rotating plate is in proportion to the amount of solid waste and we estimate the regional solid-waste amount by distributing the weight from the operating duration of the rotating plate. Figure 3 shows a simple example of this approach.

The examined rear loader type garbage truck operates its rotating plate and packer blade by using a power take-off (PTO). The engine speed and vibration pattern are switched when the rotating plate and packer blade are operated. The



	Area A	Area B	Area C	Total
Collection duration	20 min.	10 min.	10 min.	40 min.
Estimated garbage weight	100Kg	50Kg	50Kg	200Kg

Figure 3. Garbage amount estimation

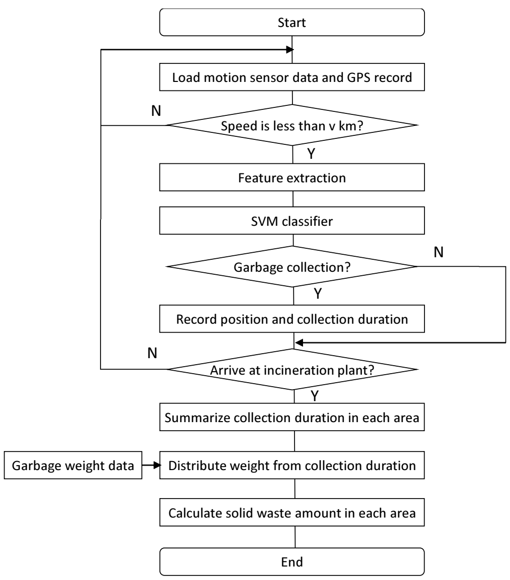


Figure 4. Flowchart of proposed solid-waste amount estimation

proposed method recognizes the difference in the vibration pattern using a motion sensor.

We also discuss a method that estimates the regional solid-waste amount from the trip times for each area using only GPS records. However, with actual garbage collections, narrow roads require additional time to allow the garbage collector to reach a secluded collection site on foot. Alternatively garbage collectors may be able to load large amount of solid waste quickly at a large collection site in a large apartment. Thus, it is difficult to estimate regional solid-waste amounts in detail using GPS records.

Moreover, we also discussed a method using sound to detect rotating plate operation and a method by garbage bag detection from camera image. However, these methods require additional devices outside of the truck. In addition, these microphone and camera approaches may violate citizens' privacy by capturing their voice and face. Our method can be implemented by using a recent smartphone equipped with motion sensors and it is easier to install in a garbage truck.

A. Garbage collection duration detection using motion sensor

Figure 4 shows a flowchart of our proposed method for estimating the amounts of solid waste.

1) Garbage-truck motion measurement: We mounted motion sensors on garbage trucks and measured garbage truck

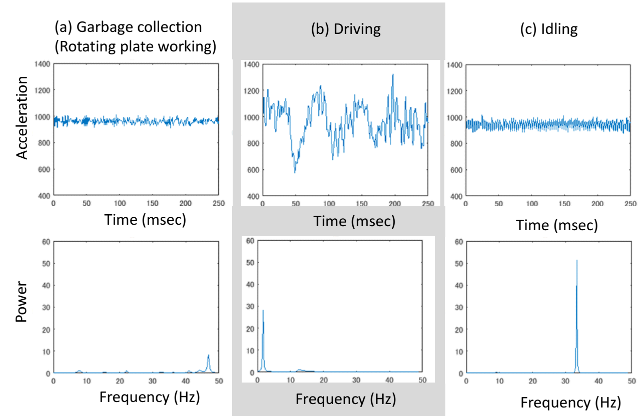


Figure 5. Acceleration sensor data and power spectrum

vibration. In the proposed method, acceleration data and gyro data are adopted. Figure 5 shows examples of acceleration sensor data and their power spectra. As the figure shows, we can find different peak acceleration frequencies depending on the garbage truck's situation (collecting garbage, driving, or idling). The peak frequencies differ according to the engine speed in each situation. We collected motion sensor data at 100 Hz, because the peak frequency during garbage collection was approximately 45 Hz.

2) Feature Extraction: Feature vectors are generated from motion sensor data by applying a sliding window framework. In the sliding window framework, features are calculated on N sample windows of sensor data with M samples overlapping between consecutive windows. We decided on $N = 1024$ and $M = 100$ in the latter evaluation. The sliding width M corresponds to the interval of GPS records.

LPC (Linear Predictive Coding) based cepstrum coefficients for each axis of the acceleration sensor data are extracted as features. LPC-based cepstrum coefficients are commonly used for speech recognition. We use the variations in the cepstrum coefficients obtained with the motion sensor depending on the situation of the truck. The feature extraction method is based on [4] where we provide more details.

3) Labeling: We selected a typical garbage collection day and annotated the sensor data with a "rotating" label. "Rotating" means that a garbage collector is operating the rotating plate. Closing door vibration causes a large noise regarding rotating duration detection. A garbage collector sometimes closes the door while another garbage collector is loading garbage. Thus, we do not annotate "rotating" labels to avoid the effect of the noise.

We annotated the labels by listening to sound recorded by microphones mounted on the garbage truck.

4) Supervised learning: We adopted SVM (Support Vector Machine) with a polynomial kernel as a classifier. We selected the same numbers of feature samples randomly for "rotating" and no-label.

We assume that the garbage bags are loaded on the garbage truck while the truck is stationary. We calculated the speed of the garbage truck using GPS records, and selected feature vectors whose speed was less than v km. We used $v = 10$ in the latter evaluation.

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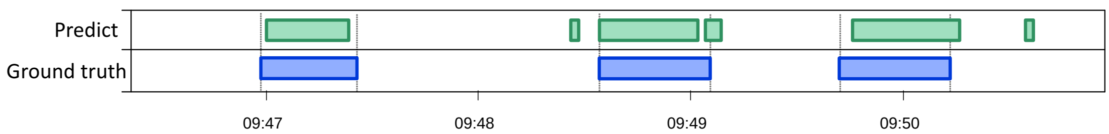

Figure 6. Part of garbage collection duration estimation result

TABLE I. RECOGNITION RESULT

		Recognition result		
		Rotating	No-label	Accuracy (%)
Ground truth	Rotating	662	138	82.8
	No-label	63	737	92.1

5) Garbage collection duration detection: The garbage collection duration is estimated by aggregating time samples classified as “rotating” by the SVM. We record the detected garbage collection duration and its locations. When the garbage truck arrives at the incineration plant, we summarize the data and then estimate the amount of solid waste by region as described next.

B. Estimation of solid waste amount

We estimate the amount of solid waste by region using the solid waste weight measured of incineration plants. We assume that the operating duration of the rotating plate is proportional to the amount of solid waste. We calculate the amount of solid waste by region by distributing the weight from the operating duration of the rotating plate. We total the amount of solid waste in each city block or each resident association.

VI. EVALUATION

First, we extracted feature vectors from acceleration and gyro sensor data and annotated them using sound data recorded by microphones mounted on the outside of the garbage truck. Then, we evaluated the recognition accuracy of the estimated garbage collecting duration.

We selected two days’ motion sensor data where the same garbage truck collected the same type of solid waste. The garbage truck collected combustible waste during the morning. We selected 400 labeled feature vectors randomly for each label (“rotating” and no-label) and for each day.

Table I is the confusion matrix of cross-validation using 3-axis acceleration sensor data and 3-axis gyro sensor data. We created a classifier by using one day’s motion sensor data and tested the motion sensor data of the other day. The precision was 88% and the recall was 87%.

Figure 6 shows the result of our garbage collection duration estimation. Some errors occurred at the start and the end of the garbage collection. Developing a post-processing technique to reduce estimation error is our next goal.

The result shows that the proposed method can accurately recognize garbage collection duration. However, we used motion sensor data from just one garbage truck in this evaluation, and the garbage was all the same. Further evaluation of, for example, difference between garbage trucks and the difference between different types of garbage constitutes our future work.

VII. CONCLUSION AND FUTURE WORK

In this paper, we proposed a garbage collection duration detection method and a framework for solid waste estimation using the detected duration and total solid waste weight. We also reported a preliminary experiment and showed that the proposed method could detect the garbage collection duration accurately for one garbage truck and one type of garbage.

As the next step in this research, we plan to evaluate the proposed method in more detail and extend the method to detect garbage collection durations for multiple types of garbage trucks and multiple types of garbage. We will also develop a post-processing technique to reduce noise such as the vibration of a closing door. Moreover, we are planning to create a system to feed back the estimated regional amount of the solid waste to citizens and to examine the effectiveness of our proposed approach for waste reduction.

ACKNOWLEDGMENT

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Deep on Edge: Opportunistic Road Damage Detection with Official City Vehicles

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***Abstract*—How can we inspect city conditions at low costs? City infrastructures, such as roads, are elements of great importance in urban lives. Roads require constant inspection and repair due to deterioration, but it is expensive to do so with manual labor. Therefore, these works should be done automatically so that the cost of inspecting or repairing becomes cheap. While there are several works to address these road issues, our study focuses on official city vehicles, especially garbage trucks, to detect damaged lane markings (lines) which is the simplest case of road deterioration. Since our proposed system is implemented on an edge computer, it is easy to attach our system to vehicles. In addition, our system utilizes a camera, and since garbage trucks almost run through the entire area of a city every day, we can constantly obtain road images covering wide areas. Our model, which we call Deep on Edge (DoE), is a deep convolutional neural network which detects damaged lines from images. In our experiments, to evaluate our system, we first compared the accuracy of line damage detection of DoE with other baseline methods. Our results show that DoE outperforms previous approaches. Then, we investigate whether our system can detect the line damage on a running car. With this demonstration, we show that our system would be useful in practice.**

Keywords–Smart City; Deep Learning; Edge Computing; Image Recognition;

I. Introduction

The road is one of the most important infrastructures of a city in planning and development. For instance, people usually use them for going somewhere or for planning land utilization to enrich their livelihoods. However, many roads need repairing since most of them are built in periods of rapid economic growth and have been deteriorating since. Thus, to inspect their condition for road repair, the city administration needs to employ people for constant inspection. Yet manual road inspection is expensive and takes a lot of time; for instance, in order to detect the damage or blur of road markings, people have to check by eye, whose ability has certain limits. In addition, in certain regions such as Japan, public funds for road inspection have been reduced due to current societal conditions. In short, manual road inspection and repair is not enough for sufficient maintenance.

Most previous work has therefore focused on making the cost of road inspection cheaper to increase sustainability. Some works have focused on road flatteness [1]–[3], potholes [4] [5], and cracks [6]. In contrast, we aim to detect the damage or blur of white lines. To our knowledge, only our previous work addresses this problem [7]. Detecting the damage of white lines is difficult to do using smartphone accelerometers such as [1]–[3]. Thus, we use a camera to take pictures/videos [6] [7]. If

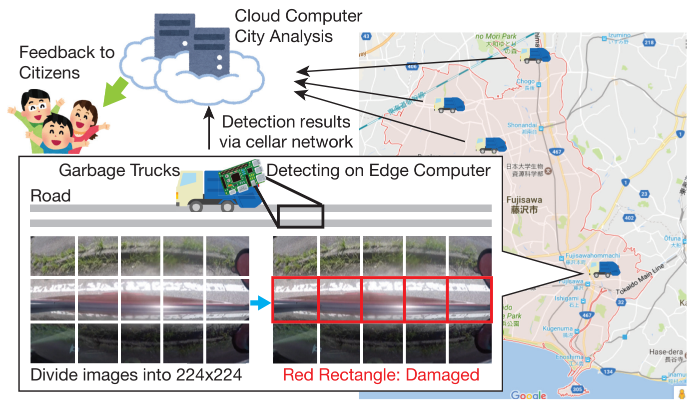

Figure 1. Our system overview. Each city vehicle running in the city detects white line damage. The cloud computer aggregates the results from them and monitors the city.

we use participatory sensing [8] as well as [6] and collect the images, however, the cost issue still remains due to the cost of platform introduction and labor.

To tackle this issue, we focus on city vehicles, especially garbage trucks. Since garbage trucks run their services every day and cover a whole area of the city, if the garbage truck equips a camera and takes pictures of roads, we can obtain road images from the whole area. Furthermore, we do not have to pay additional costs for labor or facilities. However, the number of running garbage trucks is so large (e.g., hundreds of trucks) that it is troublesome to storage and manage image data in a centralized way. Simultaneously, if we upload an image every time a camera takes pictures, it would take great communication costs and bandwidth. In summary, our goal is proposing a system that can be attached to garbage trucks and detect white line damage on the spot.

In order to achieve our goal, we introduce Deep on Edge (DoE), which integrates edge computing and deep neural networks. The overview of our system is depicted in Figure 1. DoE consists of an edge computer (e.g., Raspberry Pi 3) with a camera to be attached to garbage trucks. When DoE detects line damage, the results are reported and sent to cloud computing. Then, we use those reports and understand city condition. We treat the task of line damage detection as a classification problem. We train a convolutional neural network (CNN), a type of deep neural network, on labeled images on a GPU server. At inference time, DoE is loaded on an edge computer and outputs a discrete probability distribution,

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assigning each image a likelihood that the white line in the image is damaged. There are some constraints to using DoE on edge computers due to restricted performance, while on the other hand we do not have to consider the number of parameters or inference speed when we use DoE on a high-performance computer. So to use DoE on edge computers, we design the CNN architecture to be as small as possible but to keep the accuracy high. To evaluate DoE, we compared it with baselines on the line damage detection task. As a result, DoE outperforms baselines on this task while reducing the number of parameters. Simultaneously, we visualize DoE activation so that we can understand how it has learned to detect line damage.

The contributions of the paper are summarized as follows:

- Propose the system, called Deep on Edge, which integrates city vehicles, edge computing, and deep convolutional neural networks.
- Pose lane marking (line) damage detection as a classification problem and proposing our model which outperforms other baselines on this problem.
- Discuss the ability of the neural networks through activation visualization to design network architectures appropriate for practical use.

The paper is organized as follows. In the next section, we describe the white line dataset which we use in this paper. In Section III, we present our system which performs line damage detection. Then, we explain in detail the experiments and compare the results with those obtained in a previous research in Section IV. We discuss the experiment result and how DoE learned to detect line damage in Section V. Finally, we introduce related works to compare with our work in Section VI and conclude the paper in Section VII.

II. Summary of Our Lane Marking Dataset

In this paper, for detecting road damage, we focus on the damage or blur of white lines, which we assume is the most common type of lane marking. To collect line images, we attached a normal camera, which can film by 60 fps, on a side of a passenger car so that the camera always films the line. Then, we drove the car within 50km/h for four days from March 30th, 2016 to April 2nd, 2016 in daytime. Note that it was sunny days. While we got videos in which each frame is 1024×768 pixels after filming, we randomly cropped frames into 224×224 pixels. This cropping was done for reducing the training time until the model convergence and allowing the model focus on the line damage. One participant annotated those cropped images with three kind of labels; damaged line, undamaged line, and no line. After the preprocessing described above, we obtained 43000 images of lines. At our experiments, we divide the dataset to 35000:8902. The examples of our dataset are shown in Figure 2 and described in detail in Table I.

Figure 2. Dataset samples. Each image is 224×224 pixels by random clipping from video frames, respectively. The images at top row show damaged line, the images at mid row undamaged and at bottom row no line.

TABLE I. OUR DATASET WHICH WE COLLECTED, PREPROCESSED AND ANNOTATED.

Class	Type	Undamaged	Damaged	No line	Total
Binary	Train	10696	14304	–	25000
	Test	3829	5073	–	8902
Trinary	Train	15445	11568	7987	35000
	Test	3932	2957	2013	8902

III. Deep on Edge System

We pose the task of line damage inspection as a classification problem. For this, we use a dataset of images of lines with three kinds of labels described in the previous section. The input to DoE are image pixels and the target output is a one-hot vector encoding those labels. Given an image, the output of this model is a probability distribution describing the extent of road damage. The advantage of outputting a probability distribution is that this gives the model the ability to give specific scores to a line image, taking out the necessity of a human expert to give specific ratings.

A. Our Model

In order to detect line damage from images, we adopt a convolutional neural network, which is a special type of feedforward neural network or multi-layer perceptron and works well with two-dimensional images. We design our CNN by referring to the VGG16 architecture [9]. VGG16 is one of the major CNN architectures which was used to win the ILSVR competition in 2014, although it has been outperformed by great advances such as Inception [10] and ResNet [11] [12]. VGG16 only uses convolutional layers with 3×3 kernels and pooling layers with 2×2 kernels. This feature is very significant for DoE since the size of the model is required to become as small as possible to work on edge computers. Given an input image$\mathbf{X}$ of width w, height h and c color channels (usually RGB channels) represented as $\mathbf{X} \in \mathbb{R}^{w \times h \times c}$ at each convolutional layer, it is convolved with d sets of local kernels $\mathbf{W} \in \mathbb{R}^{w \times h \times c \times d}$ and bias $\mathbf{b} \in \mathbb{R}^{d}$ is added:

$$h = \phi(\mathbf{W} * \mathbf{X} + \mathbf{b}), \quad (1)$$

where $*$ denotes a convolution operation and ϕ is a non-linear function that we use the rectified linear unit (ReLU, $\max\{0, x\}$). Max-pooling, a form of non-linear downsampling, is applied to the output of the convolution. Max-pooling partitions the input into a set of non-overlapping rectangles by the kernels and outputs the maximum value in each sub-region respectively. This operation is very useful because it reduces the dimensionality of a high-dimensional (high-resolution) output of the convolutional layer and summarizes the activations of neighborhood features so that model becomes robust to local perturbations. Since our input images are filmed from a driven car, the location of lines in the image are not fixed. DoE is built by several alternating convolution layers and max-pooling layers.

In VGG16, the output after some convolution layers and max-pooling layers is flattened for the input of to the following layers, which are fully-connected. If the shape of the output of convolution is $\mathbb{R}^{w \times h \times c}$ and the output dimension of the next fully-connected layer is d, the number of parameters in that FC layer becomes $w * h * c * d$. This is a problem when the size of the input image is large, since the larger the image size is, the larger the number of parameters becomes. To avoid the increase in number of parameters, we use global average pooling [13] instead of flattening. Applying global average pooling allows the number of parameters in the FC layer $c * d$ to be independent of the input image size. At the last layer of DoE, the output is a probability distribution over the possible conditions of the road.

The model of the DoE architecture which we used in our experiment is depicted in Figure 3.

B. Implementation for Practical Use

While DoE is trained with the road images of size 224×224, the size of images from a video camera is much bigger than that. Although our DoE model can take any image resolution, our preliminary experiment showed that DoE cannot detect the line damage accurately at any resolution. In order to tackle this issue and use DoE for practical use, we implement a module that divides the input image into 224×224 sub-regions and reshapes these sub-regions to $X \in \mathbb{R}^{n \times 224 \times 224}$ where n is the number of sub-regions. Even if n is very large, DoE is able to process it all at once. For instance, if the size of an input image is 1280×720, the number of sub-regions becomes $(1280/224) * (720/224) \approx 15$ and the input to model $X \in \mathbb{R}^{15 \times 224 \times 224}$. Although our module crops out the top, bottom, and right sides of the image, this is not a problem because of two reasons: (a) the top and bottom sides of the image usually does not contain the road (b) the road contained on right side is contained in the next input image. Figure 3 also shows this module.

IV. EXPERIMENT

In this section, we show two kinds of experiments. First, we compare DoE with baselines which are used in previous works to evaluate DoE. Then, we examine whether DoE is fit for practical use.

A. Accuracy Comparison

In order to evaluate DoE and its architecture, we compare it with previous work [6] [7]. Although Maeda et.al [6] classify the degree of road condition into three types: “smooth (no-damaged)”, “need repair” and “not need repair”, its actual classifications are difficult to distinguish, as different outputs are produced from visually similar images. To make this problem more interpretable, we simplify this task as binary classification problem: the road which is photographed in given images is whether damaged or not. Therefore, we used the dataset we use consists of images labeled “damaged” and “undamaged” in Table I.

TABLE II. ACCURACY COMPARISON ON THE LINE DAMAGE BINARY CLASSIFICATION TASK. tHE NUMBER OF PARAMETERS IS THE SUM OF WEIGHTS AND BIAS.

Method	Acc.	AUC	Recall	Pre.	F1	Params.
Linear SVM	82.4	0.82	0.87	0.83	0.85	–
Random Forest [7]	84.0	0.83	0.91	0.83	0.87	–
AlexNet [14]	92.5	0.9833	0.92	0.92	0.92	58000K
AlexNet–(d) [6]	92.5	0.9845	0.92	0.92	0.92	1680K
AlexNet–(e) [6]	92.7	0.9859	0.93	0.93	0.93	913K
DoE (ours)	**94.1**	**0.9894**	**0.94**	**0.94**	**0.94**	**18K**

TABLE III. CONFUSION MATRIX OF DOE.

Number of Parameters 18171		Prediction: Undamaged	Prediction: Damaged	Prediction: No line	Recall
Ground Truth	Undamaged	2795	162	0	0.945
	Damaged	196	3734	2	0.950
	No line	0	1	2012	1.00
Precision		0.945	0.950	0.999	0.980

As baselines, we adopt two kinds of methods. The first method tests classic machine learning algorithms: a support vector machine classifier (SVM) that can achieve good performance at binary classification, and a random forest which can detect the line damage [7] as well as our work. The second method is a deep neural network. We choose the AlexNet which is proposed in [14] and won the ILSVR competition in 2012, and has been used quite actively since [6]. Further, since the aim of our study is road detection on an edge computer, the smaller model is desirable and we also examine the alternative models that are proposed in [6]: AlexNet–(d) and AlexNet–(e).

Before training DoE, we initialize the weights of DoE with random values and use the Adam [15] stochastic gradient descent algorithm with a learning rate of 0.0005, a momentum of 0.9 and a batch size of 32. Meanwhile, those of baseline networks use respective values of 0.0001, 0.9 and 100. We then trained models with early stopping, which is a training procedure that stops training if the error on the validation set stops decreasing.

Table II shows the experiment result. DoE outperformed baseline methods, even though the number of parameters is quite less than others. This result shows that deep architectures do not necessarily have good performance in computer vision tasks, even if it has been reported as good architecture. In short, it is necessary to tweak model architectures for specific tasks.

B. Practice Investigation

For practical use, we examine whether DoE is able to detect line damage from an actual image from a camera. For this, we retrain DoE from a binary classification problem to a 3-class classification problem; “undamaged (no-damaged)”, “damaged”, “no line”. When we use DoE that solves a binary classification problem, it may cause false detection when there is no line. The result confusion matrix of 3-class classification

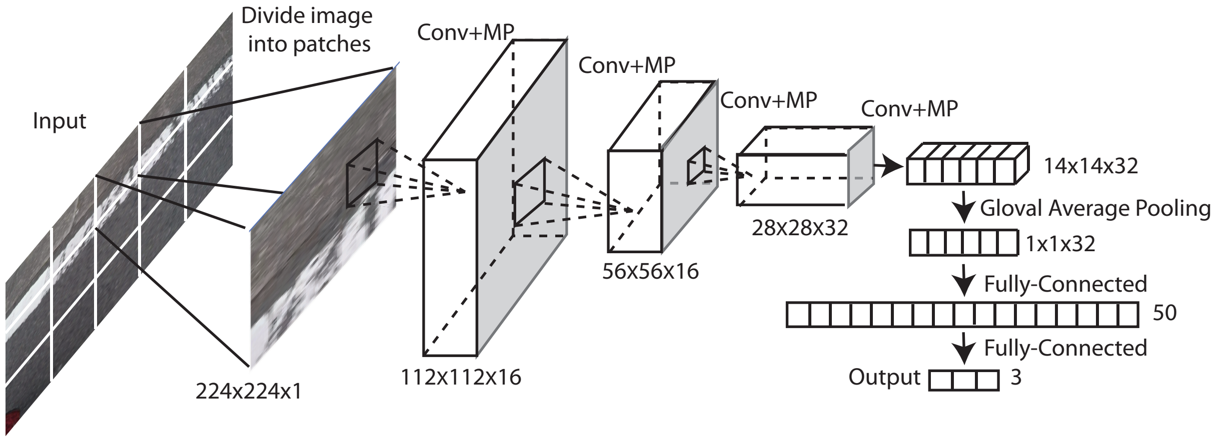


Figure 3. Our model on DoE architecture. "Conv + MP" denotes that convolutional operation with 3×3 kernels with strides 1 and max pooling operation with 2×2 kernels with strides 2. After four convolution and pooling, applying global average pooling [13].

is shown in Table III and actual detection in Figure 4. As a result, DoE can classify the road condition with 98% accuracy. Furthermore, in the case of Figure 4(a) (b), DoE classifies the patches perfectly. Note that in (b), at the location of the yellow font, the left upper patch is classified as "undamaged" correctly, while patches right side hand of it is classfifed as "damaged". On the other hand, DoE misclassifies "undamaged" patches as "damaged". This might happen if the line is dirty or something is on the line (e.g. the shoe is photographed in Figure 4(d)).

V. Discussion

A. Activation Visualization

In general, while it is said that CNNs are useful for image recognition, it is difficult to understand what the network learn. For instance, Figure 5 is the visualization of the kernel of first convolution layer of DoE before training and after. To tackle this problem, we visualize the activation of each kernel of DoE when the input damaged road image comes as shown in Figure 6. From the visualization, we can see that the model activates the part of damaged line like noisy dots, while there are only a few activated on the undamaged line. Remarkably, at the fifth layer, the activation of each unit in each image is mostly opposite. This result shows that DoE correctly learns the damage of line.

B. Input Image Generation

Furthermore, to understand the model in detail, we generate the image that DoE is likely to classify to damaged and undamaged. This method is inspired by [16]. The output of DoE is through a sigmoid function which has the asymptote $y = 0$ and $y = 1$ and the nature:

$$\lim_{x \to \infty} sigmoid(x) = 1 \tag{2}$$

$$\lim_{x \to -\infty} sigmoid(x) = 0. \tag{3}$$

Therefore, sigmoid is likely to output nearly 1 when it receives a large input and vice versa. Utilizing this nature, we can observe the output of DoE changes with fixed model parameters when we change the input. Beginning with a randomly initialized image, we use gradient ascent:

$$x \leftarrow x + \eta \frac{\partial a_i(x)}{\partial x} \tag{4}$$

to change an input image. Note that x denotes generated image input and η denotes learning rate. Furthermore, $a_i(x)$ represents the output of the ith layer and we use the last layer$i = 7$. Then, we maximize and minimize the output of $a_7(x)$ by Eq. (4). To emphasize the features which model learned, we applied Lp norm regularization:

$$||x||_p = (|x_1|^p + |x_2|^p + \cdots + |x_n|^p)^{\frac{1}{p}} \tag{5}$$

and total variation:

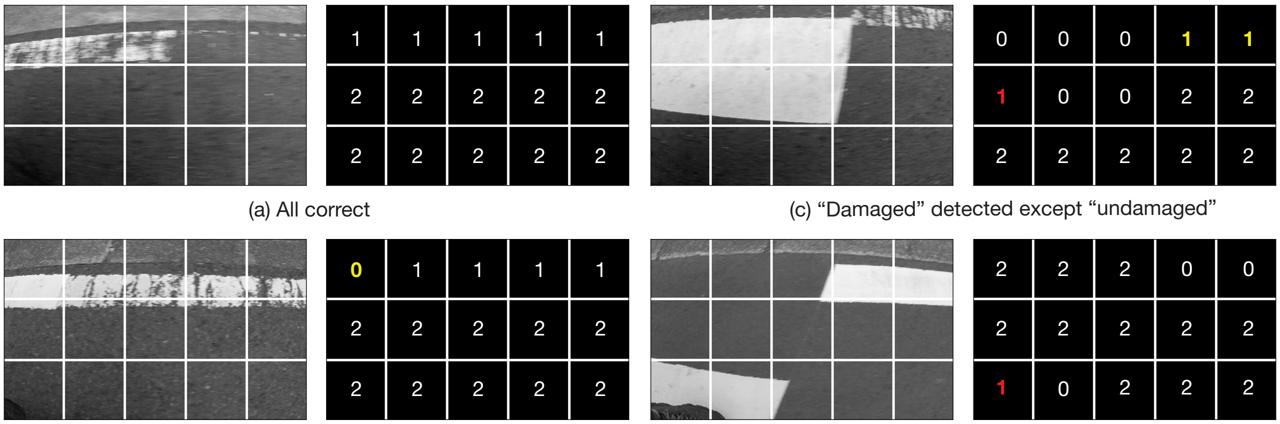
$$V(x) = \sum_{i,j} \sqrt{|x_{i+1,j} - x_{i,j}|^2 + |x_{i,j+1} - x_{i,j}|^2}, \tag{6}$$

which smoothed the images. The results are depicted in Figure 7. The image in the left of Figure 7 is classified by DoE as "undamaged", and the right image is classified as "damaged". There are much more white parts in the "undamaged" image than the "damaged" image. This shows that DoE recognizes line damage. In summary, from these visualizations, we found that DoE has learned to extract patterns and differentiate "damage" and "no damage" from the dataset, without any clues except from given labels.

VI. Related Works

Smart City. There are numerous of works that tackle city/urban problems from a point of smart city view. Zheng et.al [17] have contributed to urban energy issue and city planning by estimating the location of gas stations from the trajectories of taxis. Simultaneously, other works analyze urban livelihood from a geographic aspect [18] and detect where crime occurs [19]. These works are very important for citizens and the administration of cities to make their livelihood much better. Our work is an example of smart city work which makes transportation in cities more comfortable.

Road Inspection. From the point of the road inspection, there are a lot of points to inspect roads. One of those points is flatteness. To detect the flatteness, the use of accelerometer devices or the smartphones accelerometers is the straightforward



(a) All correct

(b) All correct

(c) “Damaged” detected except “undamaged”

(d) Detecting “undamaged” as “damaged”

Figure 4. The result of the line damage detection with actual images. Each number denotes the classes, respectively; 0: undamaged, 1: damaged, 2: no line. (a) (b) DoE classifies all patches correctly. (c) Although DoE mistakes classifying “undamaged” as “no line” (at red fonts), it correctly detects damage at yellow fonts.

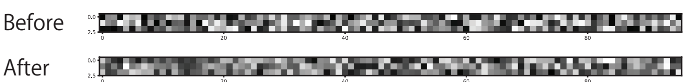


Figure 5. The visualization of kernels of first convolution layer of DoE before training and after.

approach [1]–[3]. Our goal of this study is line damage/blur detection, which is difficult to detect with accelerometers since the value of accelerometers do not change with respect to line damage. The other point of roads inspection is cracking. Concurrent to our method, Maeda et.al [6] used deep CNNs to detect road damage from images which are uploaded by citizens. Although they succeeded in detecting road damage on the application of smartphones, the model size is still too large to work on edge computer because of insufficient RAM. Furthermore, they relied on people to give image data, which is called *participatory sensing* [8] and depends on the motivation of participants. While there are numerous works to invent the incentive to make people more likely to participate [20] [21], the cost to offer the platform for participatory sensing still remains a problem. In contrast, we propose a system which collects images by using city vehicles, so that constant image data comes in daily.

The Aspect of Deep Learning. In order to run DoE on edge computers, a small model size is preferred. In the aspect of model compression, there is a lot of approaches [22] [23] and those are in progress. While our system divides the images into 224×224 patches in order to let DoE focus on the line, a model with an attention mechanism can be introduced to find the place where it should focus on in the image [24] [25]. Furthermore, while DoE classifies whole images, semantic segmentation [26] [27] can perform pixel-wise classification. In summary, we designed DoE to be simple, but there are a lot of improvements which can be made using new architectures.

VII. Conclusion

We presented DoE, a system that detects line damage via deep convolutional neural network working on an edge computer. Regarding the problem as a classification task, DoE produces a probability distribution over possible road conditions. This allows it to express its uncertainty about the damage of road. While previous work focused on detecting road flatteness, potholes or cracks, DoE is able to detect the damage or blur of lines. Our experiments show that DoE outperforms other methods for road damage detection, even though it has less parameters than other models. We further investigated how DoE learns to detect line damage by visualizing their activations over certain kinds of images, and generating images which the system is more likely to estimate as having damage. Furthermore, we show that it is practical to attach DoE to official city vehicles.

Acknowledgment

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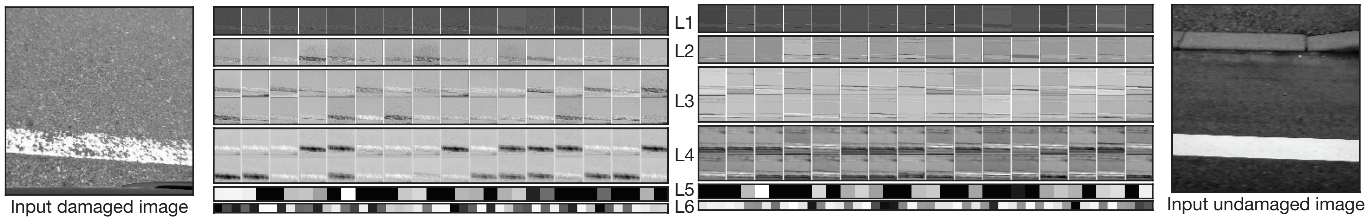

Figure 6. The visualization of the activation of each layer when the damaged line and undamaged line input images come. Remarkably at the fifth layer, each activation is active oppositely.

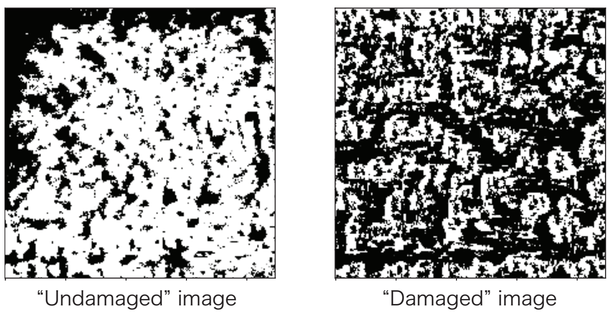

Figure 7. The examples that are generated to let DoE more likely to classify as “undamaged”, and vice versa. There are more the white parts in “undamaged” image than “damaged” one.

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Towards Understanding Latent Relationships among Uncollectible Garbage and City Demographics

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***Abstract*—We propose a preliminary work of a GIS-based participatory sensing system for collecting city information which works with a real-time collaboration of local government employees. With garbage management data collected by our application, we provide the running results of spatio-temporal data analysis that uncover the latent relationships among the spacial distributions of uncollectible garbage and city demographics. To discover such relationships, we conducted simple experiments that predicted the amount of uncollectible garbage from demographic and housing statistics by regularized linear regression methods and show that utilizing both population and housing statistics improved the predictive performance. We also report that the features of population and housing statistics, which are related to the lifestyles of citizens, greatly affect the amount of uncollectible garbage.**

***Keywords*–Participatory sensing, Data mining**

I. Introduction

Understanding the relationships between citizen's activities and an urban information (e.g., types of housing) is one critical topic for both citizens and governments. These relationships could provide an understanding of cities from various viewpoints, so that we can utilize knowledge for urban management, urban planning and so on. For example, Budd [1] studied what type of house burglaries could be predicted from official British crime data. In a more recent study, Venerandi et al. [2] proposed a quantitative method to study the relationship between gang activity and a set of descriptors of urban forms extracted from open datasets for areas in London. Since providing security and safety are important for cities, these observations should encourage more practical urban planning.

In this paper, we focus on finding the relationship between garbage and urban information, including demographics and types of residences. Waste management and recycling are typical worldwide problems in various cities and countries for improving public health and reducing environmental footprints [3], [4]. In addition, since the cost of garbage management in cities is enormous (e.g., Fujisawa city in Japan annually pays more than seven billion yen for garbage-related city operations), garbage reducing initiatives are required for a city to be cost-effective [5]. Thus, the final goal of our research is to provide valuable knowledge for cities to reduce such management costs by analyzing the relationship between garbage and urban information.

Our paper tackles two challenges: collecting fine-grained garbage information in realtime and analyzing the latent relationship between the collected garbage information and the urban information. In most Japanese cities, the information about daily garbage amounts is measured and available only at garbage centers. There is no detailed information on collected garbage for each area of a city. Moreover, several types of specific garbage, such as illegally-dumped or uncollectible garbage, require a special cost on garbage management. However, such information has not been collected or stored at all. Thus, we propose a new system called MinaRepo that collects such information by participatory sensing of the daily tasks of city employee. Secondly, we investigate the basic statistics of the garbage data collected by MinaRepo and urban information. Then, we conduct a regression problem that predicts the amount of garbage in urban sites based on the population and the housing statistics of Fujisawa city and we identify the latent relationships among garbage and city demographics.

In summary, contributions of the paper are as follows:

- We introduce MinaRepo, a new way to collect fine-grained garbage-related information by piggybacking on the daily tasks of city employees.
- We reveal the latent relationships among garbage-related information and city demographics based on statistical machine learning methods.

II. Related works

Various kinds of attempts on urban waste monitoring, management, and its related technologies can be found in [6] and references therein. Recently, a remote sensing system has become a popular technology in those research topics. A combination of remote sensing and machine learning method was proposed by [7]. They conducted a linear regression problem to estimate the amount of solid waste produced by commercial activities on urban sites, but no population and household statistics were considered in their analysis.

Great efforts have been made to improve and deploy participatory sensing technology [8]–[10].These works show the possibility of participatory sensing involving the citizens. In contrast to these works, we especially focus on city officers

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as target users. In addition, our purpose is to provide efficiency to their daily works to gather a lot of data with correct labels.

In the context of sustainability of cities and environment, statistical analysis methods were utilized to detect relationships between recycling and consuming behaviors [11], [12]. However, those articles did not focus on revealing relationships among uncollectable garbage and city demographics and adopted participatory sensing technologies for gathering datasets.

III. MINAREPO

A. Expert Crowd Sensing

To understand a citys situation or its citizens activities, it is necessary to obtain various city related information generated by citizens. One way to get such information is by monitoring the daily works of city administrative employees because they are the ones dealing with city information and citizens demands on a daily basis. For example, Fujisawa city has about $3,500$ local government employees, some of whom work outside of city hall, in areas such as garbage collection, firefighting, or maintaining city infrastructure like roads. By integrating their daily works with city sensing, large amounts of useful data can be collected every day. We call such piggyback sensing on the daily work of city employees *Expert Crowd Sensing*. In addition, city employees are expected to have more task specific knowledge of the city in which they are working than general residents. For example, garbage collectors, who daily travel through their assigned area, should be knowledgeable about the whole area and could detect subtle changes in a city. Consequently, expert crowd sensing enables us to acquire more accurate human sensing data with greater sensitivity. To achieve expert crowd sensing, a sensing tool must satisfy the following requirements:

- Easy integration with the daily responsibilities of city employees
  To enhance their daily work by such sensing, the tool must not disturb their current daily activities and has to efficiently support them.
- Easy usage
  Since most city employees are not information technology experts, our tool has to be easily understood and simply leveraged.
- Providing reliability, dependability, and security
  The tool must be used in daily city functions, which sometimes provide critical services for citizens. Reliability and dependability are also needed for it. Since city tasks often deal with the private data of citizens, data must be securely protected.

To satisfy the above requirements, we took an approach of user-engaged system development. We first interviewed city employees about the details of their work flow in their daily works and what kind of problems they presently face. We also specified the types of city data that can be collected by their works. After designing and implementing a prototype system, city employees reviewed it and gave feedback to us. Then, we reflected on such feedback and incorporated it into our system. Such user-engaged development and refinement were repeated several times.

B. System Design and Implementation

Through user-engaged development, we developed MinaRepo, an expert crowd sensing system that satisfies the above requirements. MinaRepo is composed of smartphone applications and server-side software. Fig. 1 represents its usage flow. If a city employee notices incidents that should be reported, he/she opens the MinaRepo application of his/her smartphone/tablet. First, he/she selects the type of a report based on such city incidents as illegally-dumped garbage, graffiti, uncollectible garbage, road damage, and so on. Then he/she takes a photo of the city incident and inputs a brief description for the report: ”these garbage items are plastic bottles and are not allowed to be dumped in this area.” At the same time, the GPS(Global Positioning System) location information is automatically added to the report. After inputting the needed information, he/she sends the report to the MinaRepo server, where it is stored in a secure database. The report can be accessed by a web interface, which visualizes all the reports with tables and a map interface, where city employees can check the details of all reports by clicking on the report item. In addition, the web interface provides a search functionality and filters the reports by type, reporter’s name, or date. If an additional action is needed (e.g., erasing graffiti or disposing of illegally-dumped garbage), city employees can contact the appropriate city officials.

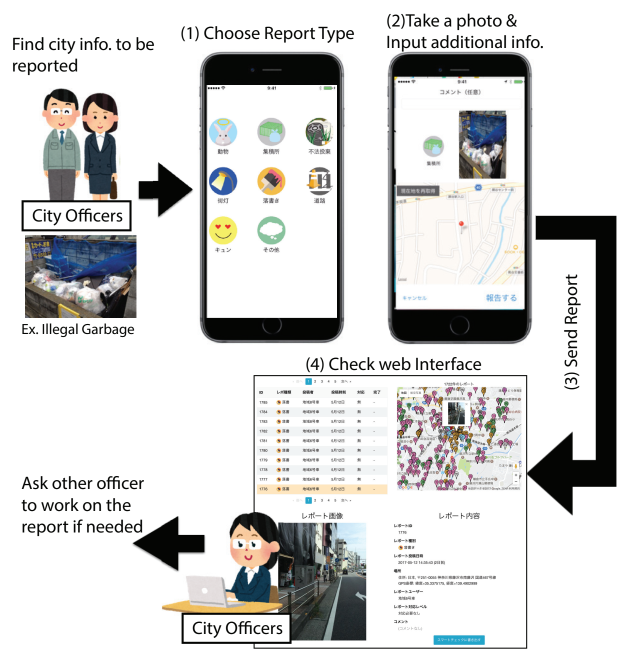

Figure 1. Overview of MinaRepo work flow

We first started to collaborate with the garbage-collecting section of Fujisawa city. Through engaged development, we confirmed that the work flow must comfortably fit their daily works. Usually, those reports are shared among city employees in traditional analog ways; when a city employee notices a city incident, he phones a manager and describes it. Then the manager records it in a map document and faxes it to another employee. This traditional procedure is time-consuming and wastes human resources. MinaRepo enables city employees to report city incidents easily and efficiently.

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We defined seven types of reports for the sensing tasks of the garbage section and identified three types of actions needed in their work: urgent action is needed, action is needed but not urgent, and no action is needed. We also provide an interface with which to choose the type of action required for a report. When an "urgent action is needed" report is input, an e-mail, which includes detailed information of the report, is automatically sent to city personnel. This functionality increases efficiency.

For providing system reliability and dependability, we also developed automatic system monitoring and backup functionality. When our systems is out-of-use, city employees can get status notification by e-mail so that they can work using their traditional procedures.

IV. Summary of the MinaRepo Dataset

Our dataset, which consists of $1,173$ reports recorded from October 6, 2016, to April 25, 2017, includes seven types of labels. The first label, residue, reports garbage that was dumped or discarded in the wrong place or on a wrong day. The second label, forgotten-garbage, is legal solid waste that was overlooked by the garbage trucks. The third label, illegally-dumped garbage, is solid waste that cannot be legally picked up in Fujisawa city. The fourth label, garbage-station, indicates a report about garbage problems at the specially designated drop sites. The fifth label, graffiti, reports a place where graffiti has been written on walls or buildings. The sixth label, animal corpse, denotes where an animals body has been found. The remaining label, disaster, report places where a relatively major incident happened and the damage caused by it. Examples of reports with residue and graffiti labels are shown in Figs. 2 and 3.

Figure 2. Photo from reports with residue label

Figure 3. Photo from reports with illegal grafitti label

Reports were submitted by 55 users. The average number of daily reports was 8.65. We show the numbers of reports by label and user in Figs. 4 and 5. Residue labels were the most frequently reported type. Graffiti reports were the second largest type. Fig. 5 indicates that our system works with users of different activity levels, including highly active users whose number of reports are in the hundreds. In contrast, about 63% of the users submitted fewer than ten reports in this period because they had just started to use our application.

The time series plot of the numbers of reports is shown in Fig. 6. One particular day got more than 100 reports because on that day the local government was sponsoring a special campaign to detect graffiti. The Lag-N autocorrelations of this time series with $N = (1, 2, 3, 4, 5, 6, 7)$ were $-0.07, 0.29, 0.19, -0.01, -0.02, 0.02$, and 0.27, respectively. Thus no significant autocorrelation was found from this dataset. We also checked the spatial autocorrelation of each label. The spatial autocorrelations for the ratio of each label by population were calculated on 192 areas of administrative districts with K-nearest neighbor graphs ($K = 4, 5, 6, 7, 8, 9, 10$). Moran's I value with the highest absolute value and its p-values for each label are shown in Table I. The residue label got a positive spatial autocorrelation, and its p-value was smaller than 0.01. Thus, reports with this label are suitable for detailed statistical analysis.

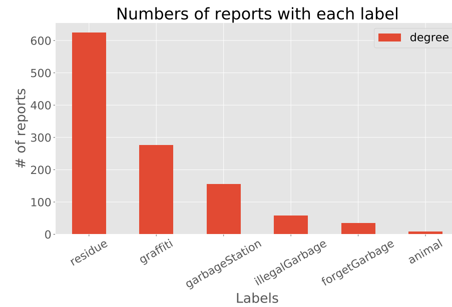

Figure 4. Number of reports with seven labels

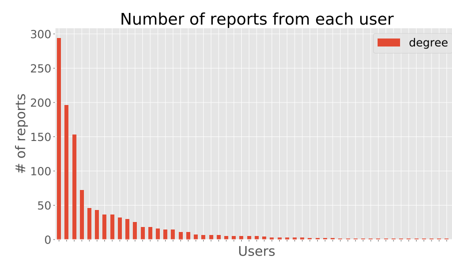

Figure 5. Number of reports from 61 users

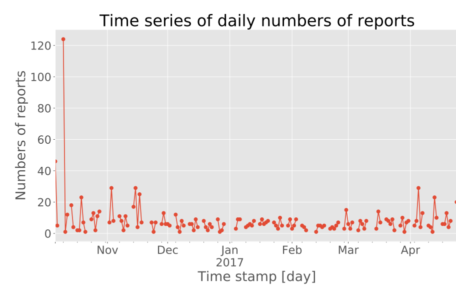

Figure 6. Daily reports submitted on weekdays

TABLE I. Spatial autocorrelation of each label

Label	*Moran's I*	*K*	*p-value*
Residue	0.154	6	0.000022
Graffiti	0.075	5	0.030596
Garbage-station	0.116	4	0.005596
Illegal-dumped Garbage	0.025	3	0.290003
Forgotten-garbage	0.035	4	0.197829

We utilized the demographic and housing statistics and describe basic summaries to understand the spatial demographics in this city. Housing statistics consisted of information about rental properties, such as identifying whether they are condos, apartments, or houses. From this dataset, we obtained 87 features that include the number of renting rooms, the average housing prices, average occupied areas, and so on. Other characteristic features also seem to have correlations

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with the amount of uncollectible garbage, for example, information about eligible renters, since some rooms can only be inhabited by one person, and such convenient amenities, including automatically locking doors, lockers for deliveries, and access to the internet. We averaged these values for each site. To compare our dataset and these statistics, we illustrated the amount of residue per population, the spatial density of the population, and the number of apartments per area in Figs. 7, 8, and 9.

V. EXPERIMENTS

We conducted experiments that predicted the amount of uncollectible garbage with residue label by population on each site. We employed linear regression methods: Elastic Net, Lasso, Ridge, and Ordinal Least Squares (OLS) [13]. We denote the target values, input values, and coefficient vectors as $y_n \in \mathbb{R}$, $\boldsymbol{x}_n \in \mathbb{R}^d$ for $n = (1, \cdots, N)$, and $\boldsymbol{\beta} \in \mathbb{R}^d$, respectively. Then, we defined the linear regression problem with both the $\ell 1$ and $\ell 2$ penalty terms as:

$$\min_{\boldsymbol{\beta}} \sum_{n=1}^{N} \|y_n - \boldsymbol{\beta}^\top \boldsymbol{x}_n\|_2^2 + \lambda_1 \sum_{i=1}^{d} |\beta_i|_1 + \lambda_2 \sum_{i=1}^{d} \|\beta_i\|_2^2,$$

where we denote the hyper parameters as $\lambda_1, \lambda_2 \in \mathbb{R}$. When $\lambda_1 \neq 0$ and $\lambda_2 \neq 0$ this method corresponds to Elastic net and includes Lasso, Ridge and OLS as special cases with ($\lambda_1 \neq 0$ and $\lambda_2 = 0$), ($\lambda_1 = 0$ and $\lambda_2 \neq 0$), and ($\lambda_1 \neq 0$ and $\lambda_2 \neq 0$), respectively.

We used the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) to assess the predictive performance of these methods,

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} \|y_n - \boldsymbol{\beta}^\top \boldsymbol{x}_n\|_2^2},$$

$$\mathrm{MAE} = \frac{1}{N} \sum_{n=1}^{N} |y_n - \boldsymbol{\beta}^\top \boldsymbol{x}_n|.$$

We employed three types of input features in our experiments in which we used housing statistics ($d = 87$), and population statistics ($d = 12$), and both ($d = 99$) were used as inputs. We randomly picked 80% of the 192 sites as a training data set and used the rest as a test dataset. Hyperparameters λ_1 and λ_2 for the regularized linear regression methods were selected by one-leave-out cross validation. We ran 10 experiments and got the average and the standard deviations of the predictive errors.

We show the experimental results in Tables II and III. Ridge achieved the best predictive performances on RMSE and MAE. Utilizing both the housing and population statistics improved the performances over just using the housing or population statistics.

To check the effects of the input features, we show the coefficient values learned by Ridge in Fig. 10. We also show the top 15 highest or lowest coefficient values and their correlation with the target values in Tables IV and V. We confirmed that the features of the housing statistics obtained the highest and lowest coefficient values among the features whose correlation was also high or low. We found various kinds of input features, which might indicate the relationship

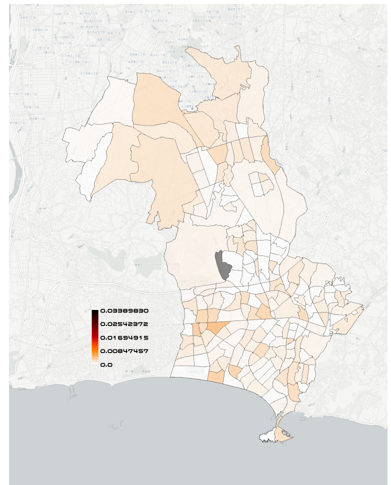

Figure 7. Amount of residue per population

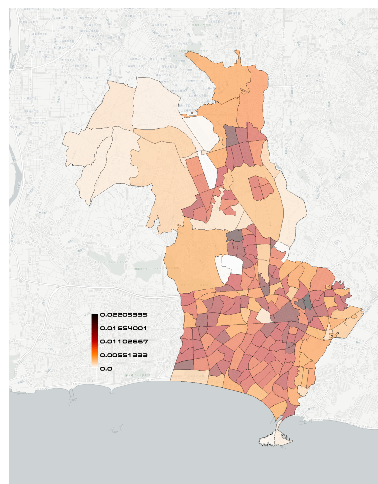

Figure 8. Spatial density of population

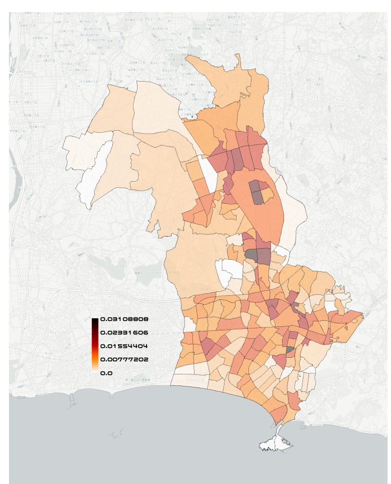

Figure 9. Number of apartments per area

between garbage and city demographics, in Tables IV and V. For example, housing characteristics, such as home security companies, single-rentals only, self-locking doors, and free internet, all of which are favored by young people living alone, got the highest coefficient values. The ratio of 30's and 50's inhabitants, which were features of population statistics, obtained high values. On the other hand, different features such as apartments that allow room-sharing also had high values. This feature seems to be favored by young people with room-mates; the popularity of such room-sharing is increasing in Japan. In contrast, with Table V, we found completely contrary features in Table IV. Such housing features as condominiums, terraces, lightings, and floor heating, which seem to be favored by families or senior citizens, had lower values. Population statistics including 70's and 90's inhabitants also obtained lower values.

TABLE II. AVERAGE AND STANDARD DEVIATION OF RMSE FOR PREDICTING SOLID WASTE AMOUNTS (RMSE$*10^3$))

Method	*Housing*	*Population*	*Housing + Population*
Elastic Net	1.44(0.28)	1.42(0.28)	1.43(0.27)
Lasso	1.52(0.21)	1.51(0.20)	1.52(0.20)
Ridge	**1.39(0.19)**	**1.36(0.22)**	**1.35(0.21)**
OLS	2.44(0.69)	1.50(0.23)	2.73(0.71)

TABLE III. AVERAGE AND STANDARD DEVIATION OF MAE FOR PREDICTING SOLID WASTE AMOUNTS (MAE$*10^3$)

Method	*Housing*	*Population*	*Housing + Population*
Elastic Net	1.10(0.16)	1.08(0.17)	1.10(0.16)
Lasso	1.13(0.09)	1.14(0.09)	1.14(0.09)
Ridge	**1.07(0.09)**	**1.05(0.11)**	**1.05(0.11)**
OLS	1.73(0.26)	1.12(0.13)	1.94(0.32)

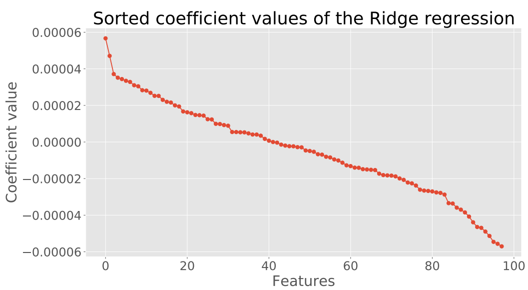

Figure 10. Learned coefficient values.

TABLE IV. FEATURES WITH HIGHEST COEFFICIENT VALUES

Feature	*Coefficient*$*10^5$	*Correlation*
Home security company	5.529	0.161
Single-rentals only	4.745	0.132
Toilet room	3.715	0.168
Bath room	3.678	0.158
30's	3.672	0.149
Room-sharing is allowed	3.408	0.087
Amounts of apartments looking for residents	3.224	0.126
Underfloor storage	3.079	0.092
Self-reheating bath	2.894	0.095
Self-locking doors	2.854	0.087
Free internet	2.545	0.075
Bathroom vanity	2.539	0.088
Pets are allowed	2.506	0.045
Tiled floors	2.329	0.052
50's	2.131	0.043

TABLE V. FEATURES WITH LOWEST COEFFICIENT VALUES

Feature	*Coefficient*$*10^5$	*Correlation*
Condominium	−5.705	−0.157
Terrace	−5.564	−0.124
Internet available at charge	−5.458	−0.177
70's	−5.133	−0.203
No room-sharing	−4.894	−0.205
Gus stove	−4.691	−0.121
Lighting	−4.645	−0.099
Free rent	−4.388	−0.101
Floor heating	−4.077	−0.097
Storage loft	−3.849	−0.179
Roommates are allowed	−3.697	−0.087
Access to parking	−3.59	−0.088
90's	−3.362	−0.143
Connected to sewage	−3.343	−0.045

VI. CONCLUSION

In this paper, we proposed a novel application for gathering information on uncollectible garbage in a city. We also showed the basic summaries of our dataset and visualized information such as housing and population statistics. To understand the relationships between garbage and demographics, we conducted simple regression problems and discovered a set of features that increases or decreases the amount of uncollectible garbage.

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Analysis of Public Vehicle Use with Long-term GPS Data and The Possibility of Use Optimization

—Through Working Car Project—

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***Abstract*— Public vehicles are considered a valuable resource, as increasing attention has been paid to the effective use of government owned resources. In addition, the development of on-board road surface condition detector and car sharing are also considered valuable activities. Though the utility potential of public vehicles is likely high, no full-scale data analysis at municipality level exists. In this study, we analyzed the extensive data collected by the "working car project" that was established in 2014 by the National Institute of Information and Communications Technology (NICT). The goal of this study is to thoroughly explore the optimum utilization of public vehicles, and discuss the potential vehicle usage patterns. Specifically, based on vehicle operation record of Kakogawa City and Fujisawa City, we analyzed the link coverage rate, assuming that the role of daily inspecting the public roads would be given to the public vehicles, and examined the vehicle use optimization and centralized dispatching system in Kakogawa City Office. The study findings indicate the potential for car sharing.**

Keywords-Data analysis; link coverage; probe car; optimization; shared car.

I. INTRODUCTION

In recent years, the movement toward the effective use of government-owned resources has increased. For example, Request for Public Facility Management Plan [1] discussed the promotion of comprehensive and planned management of government-owned resources, such as public facilities. This trend is seen in vehicle ownership as well, while the Ministry of Internal Affairs and Communications Government Efficiency Plan developed concrete measures that aim to reduce the human and physical cost on using public vehicles within the Ministry. In addition, car sharing of vehicles is also discussed in the current literature. Taguchi et al. discussed the potential of introducing car sharing in regional cities [2], Yasumochi et al. examined the implementation of car sharing in public rental housing [3], and Hara et al. discussed quasi-auction type reservation system for car sharing [4]. Accordingly, the movement toward the effective use of public vehicles is increasing.

Meanwhile, the technological advancement in vehicle use is improving. Smart IoT (Internet of Things) promotion strategy [5] published by the Ministry of Internal Affairs and Communications considered developing autonomous car to mitigate traffic congestion. In the USA, the emergence of car sharing services, such as Uber, has been widely welcomed by users [6], which is an evidence of the potential progress toward vehicle use technology development. Within this context, the National Institute of Information and Communications Technology (NICT) established "working car project" in June 2014. The project aimed at the thorough utilization of public vehicles. GPS and sensors were installed in vehicles, allowing for extensive data analysis of public vehicles.

However, no data conversion and analysis has been previously conducted for all public vehicles that belong to each city. Thus, the effective use of public vehicles belonging to municipalities is still unknown.

Therefore, in this study, we used the vast vehicle usage data collected by the working car project for Kakogawa City, Hyogo Prefecture and Fujisawa City, Kanagawa Prefecture to perform multifaceted analysis of public vehicle usage. Specifically, we calculated the operation rate and link coverage rate of public vehicles. This would be very beneficial for measuring pavement conditions during the routine operation of public vehicles. The inspection can be carried out when the public vehicles are equipped with the on-board road surface condition detector developed by Yamada et al. [7], the road surface inspection method developed by Toyama et al. [8] that considers pavement conditions of local municipalities, or the detection method of pavement wear and tear signs of Kawasaki et al. [9] that uses a general-purpose camera in public vehicles, etc.

We also analyzed the vehicle usage data from Kakogawa City to determine the least number of vehicles required for the optimum operation without interfering with work. Based on the results, we discussed the possibility of the centralized vehicle reservation system at the city office. In this manner,

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by optimizing the vehicle operation, the practical utilization of surplus vehicles such as car sharing could be discussed.

II. SUMMARY OF COLLECTED DATA

The data used in this study is summarized in Table 1. We analyzed the data that was uploaded in real time by installing smartphones in public vehicles owned by municipalities through the "working car project" established by NICT (National Institute of Information and Communications Technology) in June 2014. Because smartphones are installed in vehicles, when the engine is running, the location information is obtained at 1-s interval. In addition, we used the vehicle ledger from each municipality to obtain information about the vehicle type, usage, number of passengers, load capacity, and storage location. Details on vehicle types are provided later. In summary, there were 14 types of vehicles in Kakogawa City (4.1(4)) and five in Fujisawa City (see Table 2).

TABLE I. SUMMARY OF THE COLLECTED DATA

Target period	1/1/2016 to 12/31/2016 12/31 inclusive
Target time period	9:00–17:00
Target vehicle number	Kakogawa City (171)/Fujisawa City (99)
Data items	Longitude and latitude of vehicles at each time Vehicle ID/Vehicle type Storage location (33 locations)
Notes	Data between 12/3–12/11 is missing

III. MEASUREMENT OF INDEX WITH LONG-TERM DATA

A. Visualization of usage

For visualization of usage, Figure 1 shows the superimposed image of route information of patrol cars over the target period of one year. Though the distance traveled in one day is not high, once multiple periods are superimposed, the overall covered area becomes visible. Figure 1 shows that the patrol cars cover a wide area. Figure 2 shows the route information of each type of vehicles obtained from the records over the target period. A school bus that belongs to Shikata Kindergarten, located in the northwest corner of the city, mostly commutes in Shikata Town. This is because Kakogawa City divides the school districts by area. Garbage trucks mostly travel the main roads that connect the new clean center (garbage processing facility for the City) and recycling center. Kakogawa City government collects garbage across the whole city; however, the present data shows that garbage trucks do not travel the whole City. This is simply due to a fact that there were garbage trucks without sensors when the present data was recorded. Doctor-patient transportation vehicles also mostly travel around Kakogawa Chuo Hospital, and there is no record of travelling across the City. In addition to the reason mentioned above for garbage trucks, Kakogawa Chuo Hospital and nearby hospitals are designated for emergency patients.

Figure 1. Kakogawa City patrol car route information. Pink shows roads that patrol cars have travelled, while ocher shows roads not travelled by patrol cars.

Figure 2. Kakogawa City vehicle travel information. Red: cleaning vehicles, blue: doctor-patient transportation vehicles, green: garbage trucks, yellow: school buses

Circles in Figure 2 show associated facilities. Specifically, orange: Shikata Kindergarten, blue: Kakogawa Chuo Hospital, green: the new cleaning center (combustible garbage disposal facility), and pink: the recycling center (incombustible materials and large garbage disposal facility).

B. Operation rate

In order to evaluate the role of transportation function each vehicle plays, we calculated the operation rate. Specifically, we analyzed the travel information of each vehicle at 10-min interval. When a vehicle was moving continuously at 5 km/h or more, we considered it as in

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"operation" and calculated the number of times the vehicles "operated."

The operation rate was obtained by dividing operation times by number of business days during the target period (245 weekdays). Table 2 shows the analytical results of operation rate per usage. Though there are some differences in vehicle type classification, the mean operation rate is higher for Fujisawa City than in Kakogawa City. The analysis by vehicle type indicates that medical, patrol, and public relations vehicles are most used in Kakogawa City. The operation rate of garbage trucks is notably low in Fujisawa City. However, this is most likely because the garbage collection days and time are predetermined.

C. *Link coverage rate*

In order to evaluate the role of transportation function each vehicle plays, we calculated the operation rate. Specifically, we analyzed the travel information of each vehicle at 10-min interval. When a vehicle was moving continuously at 5 km/h or more, we considered it as in "operation" and calculated the number of times the vehicles "operated." Link coverage rate shows the value of probe car in detecting the detailed road conditions in municipalities. When we applied digital road map (DRM) data of Japan Digital Road Map Association to Kakogawa City and Fujisawa City, the obtained link rates between 25,000 and 30,000, were mostly similar. We show non-time zone link coverage rate for specific time period from the beginning of measurement (January 1, 2016). If a vehicle passes even once from the beginning of measurement, we consider that the link has been covered. Results are shown in Figure 3. Both cities showed 95% or higher link coverage rate within the one year of measurement. Operation of public vehicles can cover most of the links within one year. Therefore, it is possible to install the on-board road surface condition detector described earlier on public vehicles, thus these vehicles can routinely inspect facilities and public roads. Especially, because Figure 1 shows that the patrol cars cover a wide area, it would be appropriate to install sensors in patrol cars.

Next, we divided the business hours from 9:00 to 17:00 into eight time zones (by each hour), and considered the link for each hour as a separate unit to obtain link coverage rate. Because the traffic conditions differ depending on the time zone, obtaining the link coverage rate per time zone is valuable for traffic simulation. The results of this study are shown in Figure 4. Compared to the non-time zone link coverage shown in Figure 4, the time-zone links cannot be covered in short terms, such as a month or so. It takes a year to cover the equivalent of one month for non-time zone link coverage.

In addition, the obtained non-time zone link coverage rate for Kakogawa City and Fujisawa City is increasing in mostly the same rate.

TABLE II. OPERATION RATE ANALYSIS PER USAGE (TOP: KAKOGAWA CITY AND BOTTOM: FUJISAWA CITY)

Kakogawa City	**Number of cars**	**Operation rate**	**Kakogawa City**	**Number of cars**	**Operation rate**
School bus (Yamate Kindergarten)	2	0.0	Garbage transport	1	0.4
School bus (Shikata Kindergarten)	2	44.7	Cleaning vehicles	1	3.7
Doctor-patient transportation	1	95.1	Specialized vehicles	1	33.9
Vans	1	0.0	Collection vehicles	3	0.0
Patrol cars	2	22.7	Survey vehicles	3	0.4
Kakogawa public hall	1	5.3	Higashikakogawa Public Hall	1	20.4
Kakogawanishi public hall	1	9.0	Road patrol vehicles	1	97.1
Cargo	18	42.2	Nikkosan Cemetery	1	0.0
Shared vehicles	19	52.0	Health service vehicles	1	37.1
Small cargo	17	35.1	Crime prevention and traffic patrol vehicles	1	77.1
For on-site supervisors	1	0.4	Mankien day service transport	2	21.2
For field managers	1	0.0	Ryoso Public Hall	1	0.0
Public emergency vehicles	1	35.5	Courtesy vehicles	15	41.2
Rescue operation vehicles	1	34.7	Public vehicles (multi-purpose)	17	17.6
Public relations vehicles	1	78.0	Public vehicles (disaster prevention center)	1	31.0
Material transportation vehicles	1	14.3	Public vehicles (stadiums)	1	3.3
Vehicles for office business	6	3.5	Public vehicles (Greenery Association)	1	0.0
Mini cargo	1	22.0	Public vehicles for other uses	1	0.0
Passenger vehicles	10	25.1	Unknown	27	33.6
Garbage trucks	3	31.2	Total	91	24.5
Garbage collection vehicles	1	9.8			
Fujisawa City	**Number of cars**		**Operation rate**		
Garbage collection vehicles	75		5.2		
Patrol vehicles	13		34.8		
Cargo	11		43.7		
Passenger vehicles	28		34.6		
Road patrol vehicles	1		28.6		
Total	128		29.4		

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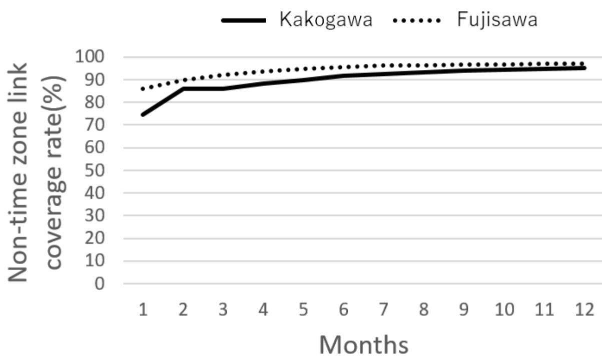

Figure 3. Non-time zone link coverage rate (Number of links: 28,917 for Kakogawa City, and 25,072 for Fujisawa City)

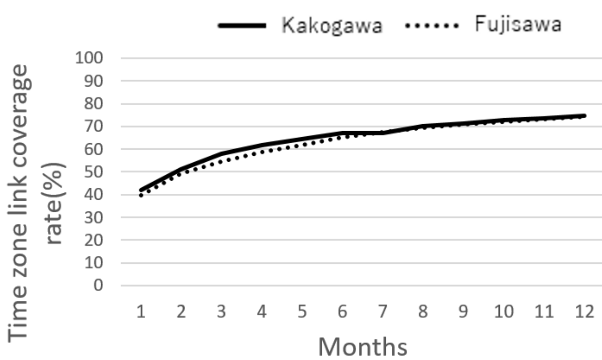

Figure 4. Time zone link coverage rate

IV. POTENTIAL DATA OPTIMIZATION

A. Vehicle operation analysis and application of optimization method for Kakogawa City

In this section, we analyze the actual travel use information of public vehicles. Without adding assumptions to usage history, we determined the least number of vehicles needed to perform the work. Furthermore, we discussed introducing a vehicle reservation system that incorporates vehicle inclusion relationship and possible usage time. We examined the potential applications of the system by applying the previously collected data to this system.

1) Data analysis

The vehicles usage data record comprises the longitude and latitude coordinates and are measured continuously. In other words, continuous tracking data precisely measured at 1-s interval is discretely stored. The storage locations and types of each vehicle are also recorded. On the basis of the obtained information, we determined whether each vehicle was at its storage location or not based on its longitude and latitude coordinate.

2) Operation optimization

We analyzed the minimum number of vehicles needed to perform the vehicle operations for each type of vehicles. Specifically, we allocated the usage history to the existing vehicles. The maximum potential usage is allocated to vehicles based on usage history (= usage is established). A new vehicle was assigned only when overlap cannot be avoided with existing vehicles. This was applied to all usage history data, in order to obtain the minimum possible number of vehicles required in operation during the target period. A schematic diagram that illustrates the operations optimization is shown in Figure 5.

Figure 5 (a) shows the usage history for vehicles A to G, with the vehicles use is divided into 5-min intervals from the beginning of the measurement for simplicity. Usage pattern during the target time is shown in shaded squares. The shading patterns show the different vehicle models, as three types of vehicles are analyzed. For operation optimization, the number of vehicles in operation is minimized by sliding the usage history, as shown in the Figure 5 (b). Vehicles C and G have overlapping use between 9:25 and 9:30, thus, this vehicle model requires two vehicles in operation.

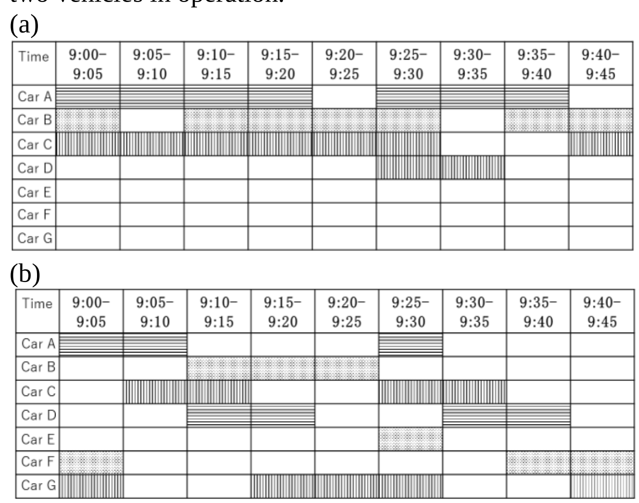

Figure 5. Conceptual diagram of operation optimization ((a): before optimization, (b): after optimization)
Translation of figures: Time, Vehicles A–G

3) Preparation of dispatch system

First, we developed a “vehicle inclusive relationship.” This is not just a dispatch table for each vehicle type, but it also includes the load capacity and the maximum passenger numbers reported in the vehicle ledger. In addition, a cross-sectional dispatch table between specific vehicles is created. Specifically, we grouped seven vehicle types (underlined) that can be substituted based on the reported usage of 14 vehicle types in Kakogawa City (mini cargo, standard cargo, small cargo, passenger vehicles, mini passenger vehicles, mini vehicles, light passenger vehicles, specialized vehicles, buses, garbage trucks (standard), garbage trucks, standard specialized vehicles, mini special purpose vehicles, and standard special purpose vehicles). In order to satisfy the usage demand for vehicles within this group, we added a condition in which vehicles that have more load and passenger capacity can be dispatched regardless of the vehicle type.

Next, we introduced the concept of "possible usage time." It implies the total usage demand for n-hour per a certain time zone. For example, a request is filed as "I'd like to use (XX vehicle) during 1 h between 14:00 to 17:00 on April 1." Usage requests collected in this manner can be shifted within the requested range so that the number of vehicles in operation is minimized. Figure 6 shows a schematic diagram of the developed dispatch system.

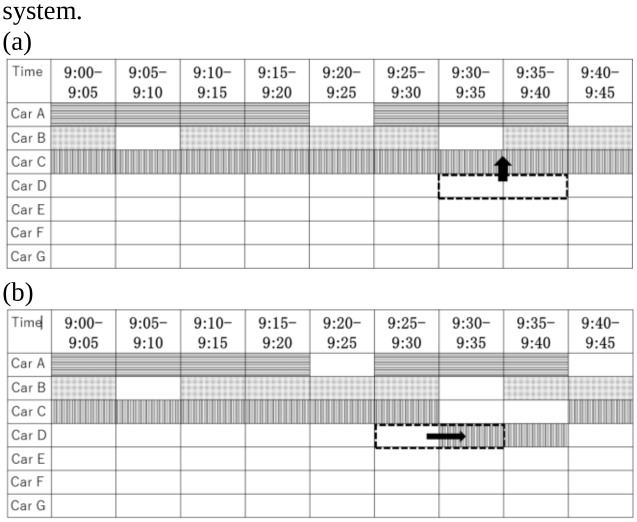

Figure 6. Schematic diagram of dispatch system ((a): shifting the reservation using the requested time, (b): vehicle dispatch table) Translation of figures: Time, Vehicles A–G

Figure 6 shows the operation optimization system assuming that the initial usage history shown in Figure 5 (a) can be shifted within 5 min of usage history. Figure 5 (b) reveals that despite that vehicles C and G are overlapping, however, the overlap can be shifted (Figure 6 (a)).

The use between 9:25 and 9:35 has been shifted to 9:30-9:40. As a result, only three vehicles are needed to operate during this time period (Figure 6 (b)).

In this section, after the initial solution was obtained by the first fit method, the tabu search technique was used to find solution heuristically by shifting tentative reservations. In other words, we extract usage history in a random order, and assign appropriate vehicles. However, if the existing vehicles cannot respond, new vehicles are assigned. In this manner, we use the tabu value of seven and maximum combinations of 1,000/step for the initially obtained solution. The calculation is completed when there is no new solution in 1,000 steps. This is how the tabu search method can be used to obtain the optimum solution.

We applied the 2016 usage history to this reservation system based on the assumption that for processing all usage history, the usage request time is defined as plus/minus 1 h from the requested time.

B. *Results*

The results of data analysis in Section 4.1 (1) revealed that there were 117 vehicles that were used at least 5 min during the period. The highest frequency of usage was detected on December 28 (Wednesday) with 192 times. On this day, the mayor toured each facility, and paid the year-end greetings. As shown in Figure 7, if the pattern of usage is analyzed per time interval, the use was most notable around 9:00–9:59 at the beginning of business hours, and around 13:00–13:59 when work restarted after lunch break.

The analytical results of operation optimization in Section 4.1 (2) indicate that 96 vehicles could be operated to cover 2016 demand.

The dispatch system analysis in Section 4.1(3) shows that by introducing the vehicle inclusive relationship system, the operation could be performed with 87 vehicles. When the vehicle inclusive relationship and possible usage time under the above conditions are applied to the analysis, the operations could be performed with 77 vehicles.

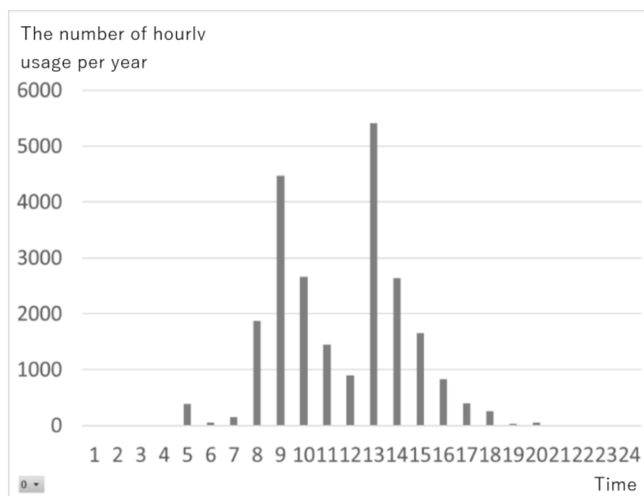

Figure 7. Frequency of usage per time zone in Kakogawa City Translation: 2016 Kakogawa City Office time-zone vehicle usage (times)(hour)

C. *Discussions*

1) *Data analysis and operation optimization*

The data analysis indicated that 44 vehicles were not used in 2016. When the operation optimization is applied, the operations, could be performed with 96 vehicles rather that 117 vehicles; thus, the number of vehicles in operation can be reduced by 31. Assuming that the annual maintenance cost per vehicle (including insurance and automobile inspection) is 60,000 yen, if the extra 75 vehicles are removed from service, the maintenance cost can be reduced by 4,500,000 yen. If those vehicles are used for car sharing, assuming they typically charge 4,000 yen/6 h, and if n% of reduced vehicles were used on each of 245 business days, the sales would be 4000 x 245 x 75 x n/100 yen. For example, when n = 20, the sales would be 14,700,000 yen.

2) Dispatch system

When the vehicle inclusive relationship and possible usage time dispatch system with uniform 1 h lee way were applied, additional 19 vehicles could be reduced by this operation optimization. It proved the benefits of applying this dispatch system.

3) Further reduction of the number of vehicles in operation

Based on the above analysis, for example, if the appropriate measures were taken to reduce the vehicle usage on December 28 (Wednesday), the number of vehicles in operation might further be reduced. This could be achieved by reviewing the routes and time frame around facilities when the maximum usage was reported. Similarly, since there is increased vehicle use around 9:00 and 13:00, measures can be taken by shifting heavy vehicle usage periods (time when vehicle use is allowed) for each department, thus, the number of vehicles in operation can be further reduced.

Although the data between December 3 (Sunday) and December 11 (Monday) is missing, and the vehicles usage information is not recorded, the study findings regarding the optimization of vehicle operations, clearly showed the potential of practically reducing the public vehicles operations.

V. CONCLUSIONS

The above data analysis examined the actual usage of vehicles owned by Kakogawa City and Fujisawa City. The analysis showed that installing the previously described on-board road surface condition detectors, can allow for the routine inspection of public facilities and roads to be carried out by the public vehicles.

We were also able to show the potential of vehicle operations optimization. In the actual optimization, differences in vehicle usage patterns in each municipality were reported, and the method used in this study may be changed slightly in future applications. However, the study also presented a basic solution for reducing public vehicles operations.

ACKNOWLEDGMENT

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