

## PAPER

# Combining Human Action Sensing of Wheelchair Users and Machine Learning for Autonomous Accessibility Data Collection

Yusuke IWASAWA<sup>†a)</sup>, *Nonmember*, Ikuko EGUCHI YAIRI<sup>††</sup>, *Member*, and Yutaka MATSUO<sup>†</sup>, *Nonmember*

**SUMMARY** The recent increase in the use of intelligent devices such as smartphones has enhanced the relationship between daily human behavior sensing and useful applications in ubiquitous computing. This paper proposes a novel method inspired by personal sensing technologies for collecting and visualizing road accessibility at lower cost than traditional data collection methods. To evaluate the methodology, we recorded outdoor activities of nine wheelchair users for approximately one hour each by using an accelerometer on an iPod touch and a camcorder, gathered the supervised data from the video by hand, and estimated the wheelchair actions as a measure of street level accessibility in Tokyo. The system detected curb climbing, moving on tactile indicators, moving on slopes, and stopping, with F-scores of 0.63, 0.65, 0.50, and 0.91, respectively. In addition, we conducted experiments with an artificially limited number of training data to investigate the number of samples required to estimate the target.

**key words:** street-level accessibility, wearable sensor, assistive technology, machine learning

## 1. Introduction

Lifeloggers are no longer burdened by heavy computers and large devices; modern lifelogging equipment is sufficiently compact and accessible for capturing all or a large portion of the life activities of wearers. Human action sensing is one of the research topics in this area. Many applications inspired by these technologies, such as context-aware services, fall detection, and daily healthcare management, have been introduced [1]–[4]. Both from the research and social points of view, lifelogging has been incorporated into many applications, many of which are available from the Android and iTunes stores [5].

This paper proposes a methodology, inspired by the recent spread of lifelogging, for the development of mobility support systems. Keeping the pedestrian pavement safe is obviously important, but outdoor environments are frequently inadequate for people with mobility impairment. One solution to the problem of reducing the burden of moving around for people with mobility impairment is to develop large-scale accessibility maps for providing accessibility information regarding the pedestrian pavement [6]. Many researchers have proposed accessibility data collection methodologies aimed at developing such maps. Most

classical and current data collection methods use official reviews by experts regarding road access. The use of geocrowdsourcing to reduce the expense is a more recent trend. However, road accessibility information sharing has been restricted to narrow spaces, such as station yards and campuses, owing to manpower limitations.

The proposed methodology overcomes this restriction by sensing accessibility information through a combination of human action sensing technologies on wheelchairs with smartphone-embedded sensors [7], [8], and machine learning [9], with the aim of developing autonomous accessibility data collection and visualization. A large-scale accessibility map can be created using machine learning algorithms that estimate accessibility information from sensor data recorded on a smartphone. Recent popular smartphones are embedded with rich sensors, such as accelerometers and gyro sensors, and their time-series data include useful human behavior patterns. If wheelchair users sense and record their driving behavior with smartphone-embedded sensors as lifelogs, then their actions, such as stopping, moving, and falling, and the status of the ground surfaces, such as smooth or bumpy, can be estimated from the time-series patterns of three-axis accelerometers. Human behavior information regarding locations at which near-falling accidents have occurred is very important in preventing wheelchair accidents while driving. Information regarding the environment surrounding wheelchairs, such as bumpy roads, is also necessary to enable users to choose maneuverable routes.

We evaluated the proposed methodology by developing a prototype system that senses outdoor activities of wheelchair users using a three-axis accelerometer mounted on an iPod touch, and then classifying sensed data using supervised learning. As estimation targets, we followed five wheelchair activities, curb climbing, driving on tactile indicators, driving on slopes, driving on flat pavements, and stopping, as indications of accessibility. Nine users were asked to drive through outdoor environments near Tokyo station with their own wheelchairs for approximately one hour each, with no limitation of action during the experiments, except driving along a designated route.

One major contribution of this paper is to propose a novel methodology for collecting and visualizing the accessibility of a pedestrian pavement using human behavior sensing technologies and machine learning. Another contribution is that we evaluate the methodology qualitatively to classify wheelchair driving performance data. We address feature extractor design and window size optimization

Manuscript received July 16, 2015.

Manuscript revised December 7, 2015.

Manuscript publicized January 22, 2016.

<sup>†</sup>The authors are with the Graduate School of Engineering Innovation, The University of Tokyo, Tokyo, 113–8656 Japan.

<sup>††</sup>The author is with the Graduate School of Science and Engineering, Sophia University, Tokyo, 102–0081 Japan.

a) E-mail: iwasawa@weblab.t.u-tokyo.ac.jp

DOI: 10.1587/transinf.2015EDP7278

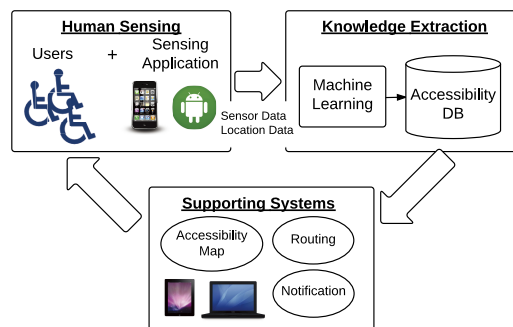
to improve the classification of wheelchair driving acceleration data and to determine the training data size required for maintaining classification accuracy. The remainder of this paper is organized as follows. Section 2 summarizes the proposed methodology and emphasizes its novelty by reviewing related work. A brief introduction to the prototype system for estimating the ground surface from acceleration data recorded from outdoor activities of nine wheelchair users, focusing on the dataset and estimation flow, is presented in Sect. 3. The results of ground surface estimation are presented in Sect. 4. In Sect. 5, we discuss the effectiveness of the proposed methodology and future directions in which to extend the prototype system for collecting and visualizing rich accessibility information, considering the experimental results and related work. Section 6 concludes the paper and suggests ideas for future work.

## 2. Street-Level Accessibility Data Collection

### 2.1 Proposed Method

Mobility is an essential element for well-being, but urban spaces and/or pedestrian environments frequently respond inadequately to the demands of people with disabilities. According to the International Classification of Functioning, Disability and Health (ICF), “Disability is the interaction between individuals with a health condition (e.g., cerebral palsy, Down syndrome, and depression) and personal and environmental factors (e.g., negative attitudes, inaccessible transportation and public buildings, and limited social supports)” [10]. Approaches to supporting the mobility disabled include helping them avoid danger or uncomfortable sites by providing accessibility information on maps [11], [12], better routes considering accessibility [13], [14], or notification regarding dangerous sites when driving. Accessibility maps are the most popular application that are useful to provide decision support for urban planners and to help wheelchair users access and select maneuverable routes in advance of driving. Karimi proposed the concept of personalized accessibility maps (PAMs) that suggest routes considering accessibility information [13]. If accessibility information is considered for routing, users can avoid uncomfortable routes.

To establish such support systems, a low-cost accessibility data collection method that requires little or no manpower is crucial. Figure 1 shows an overview of the proposed methodology with human sensing of wheelchair users and machine learning for estimating and digitizing accessibility information. A sensing application installed on smartphones records daily activity with location information as low-level sensor data. An analysis server analyzes the data according to the designed procedures, mines accessibility information, and stores it as geo-referenced accessibility information in a database. A service manager could access the accessibility database and use the data to meet the service requirements. For example, a mapping module could visualize the accessibility information on web maps, and a routing module could consider it for evaluating routes. Fi-



**Fig. 1** Overview of the proposed methodology for accessibility data collection supporting people with disabilities

nally, a user could receive the benefits of advanced services.

### 2.2 Related Work

Most frequently used or studied accessibility data collection methods are based on either official reviews or crowdsourcing. The most classical data collection method is official reviews, with local accessibilities assessed by experts, and most accessibility maps of station yards and campuses have been created in this manner [15]. This method provides very accurate information for only a small area, but checking and collecting information of large areas comprehensively is more difficult. One new trend for data collection is geo-crowdsourcing [16], [17], a methodology for collecting geographic knowledge based on crowdsourcing with little payment [18]. Many studies have proposed systems based on geo-crowdsourcing [19]–[23]. It has an advantage regarding monetary costs compared with official reviews, but it still requires substantial manpower to create large-scale accessibility maps.

This paper proposes a novel methodology for collecting accessibility information through lifelogging of wheelchair driving, benefiting from recent technological development of human behavior sensing and increasing social acceptance of lifelogging. The estimated result from human sensing data of wheelchair users who are moving along walkways, climbing curbs, or falling, might be regarded as less accurate than data collected manually, but accumulation of such results for long periods helps to increase estimation accuracy. Although many sensing apps, architectures, and algorithms have been proposed to recognize human activity from smartphone sensing data, [24]–[27], as far as the authors know, there has been no research that utilizes it in the accessibility mining context. Prandi et. al proposed a concept combining three available sources, official reviews, crowdsourcing, and sensing, and useful architectures to achieve it; however, they do not attempt to mine accessibility data from sensor data [28].

The simplest type of accessibility visualization utilizing human sensing is simple wheelchair trails. Such trails provide practical information for wheelchair users regarding wheelchair accessible areas. The information is useful but not sufficient, because such trails provide no information

regarding road accessibility; hence, users cannot determine whether a route is usable. Accessibility information can be extracted by estimation using human behavior and environmental information from wheelchair driving logs with time-series data from accelerometers. If wheelchair trails and information extracted from driving logs, such as near-falling accidents and bumpy roads, are mapped on web maps, essential support will be provided to expand wheelchair user mobility. Fukushima and colleagues [29] tried to estimate accessibility using wheelchair driving acceleration data. They converted acceleration signals into vibration acceleration levels (VALs), a route mean average of three axis acceleration values,  $a_x$ ,  $a_y$ , and  $a_z$ . The VALs were averaged for 0.1 s each and then assigned one of 13 colors to be mapped onto Google Maps. The authors checked the relationships between path states, subjective feeling, and VAL mapping, and reported that VAL conversion detects uneven pavements effectively. Our study is presented as an extension of that research to provide more objective information using machine learning technologies.

### 3. Prototype System

#### 3.1 Sensing Outdoor Actions of Wheelchair Users

As a first step in the computational estimation of accessibility information, this paper developed a prototype system with a three-axis accelerometer embedded on iPod touch and supervised machine learning for accessibility visualization. Nine wheelchair users were asked to drive their own wheelchairs with an iPod touch attached below the sheet, which sensed activity and ground surface information. The data are a combination of three-dimensional acceleration signals commonly used in human activity recognition research [30], location information, and annotation data from careful human judgment. Figure 2 shows a sensing system for the experimental data collection. The iPod touch units were attached to the right and left wheelchair tires and under the sheet and recorded the users' outdoor activities using three-axis accelerometers mounted on them. A Quasi Zenith Satellites System (QZSS) receiver was attached to the back of each wheelchair for recording locations. A video camera recorded all activities from the back of each wheelchair. The sampling rate of the accelerometer and video were 50Hz and 30Hz, respectively.

Research participants included nine wheelchair users, seven male and two female, six manual-wheelchair users, and three powered-wheelchair users, between 20 and 60 years of age. Each participant drove three laps on a designated route in the Tokyo. Figure 3-(a) is a schematic of the route, with the path inclination angle highlighted in red boxes. The route consisted of ten paths with a total length of approximately 1.5 km. To keep the experiment as natural as possible, the route was designed to cover various types of terrain without overtiring the participants. Participants traversed concrete and tile pavements, slopes, and sections with curbing stones, tactile indicators, and rough pavement

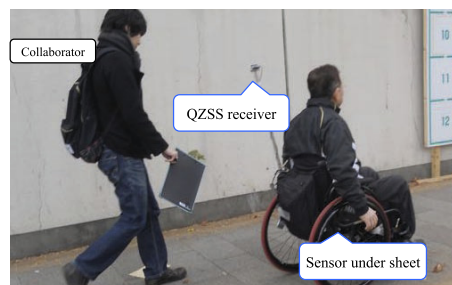


Fig. 2 Experimental sensing system and driving environment

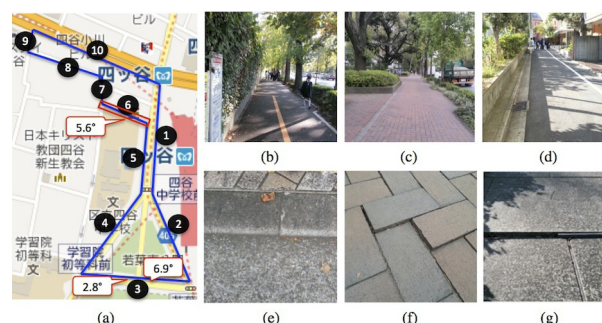


Fig. 3 (a) Route, (b) flat pavement, (c) tile pavement, (d) slope, (e) curbing stone between pavement and roadway, (f) section with rough tile pavement, and (g) section with rough concrete pavement.

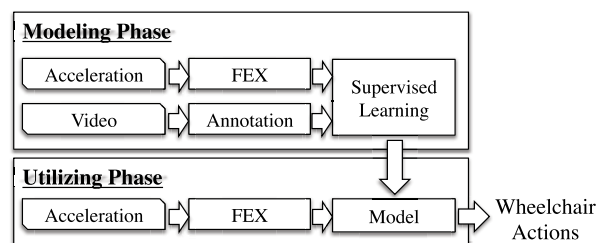


Fig. 4 Modeling and utilizing phase

(Fig. 3 (b)-(g)). Each participant drove approximately one hour to complete the route. We placed no limits on users' activities, including driving speed and positioning on walkways. Two collaborators ran parallel to the wheelchairs to ensure the safety of the experiments.

#### 3.2 Classification of Wheelchair Driving Actions

Our prototype system estimates wheelchair actions as a indication of accessibility information with a hand-made feature extractor (FEX) and a machine-made estimation model, as shown in Fig. 4 The prototype system consists of modeling and utilizing phases. The modeling phase is the step for learning correspondence relations between sensor data and the estimation target through supervised learning. The utilizing phase is the step for applying learned rules to new data for estimating ground surfaces. In the utilizing phase, the system automatically estimates ground surfaces by inputting fixed-size sensor data.

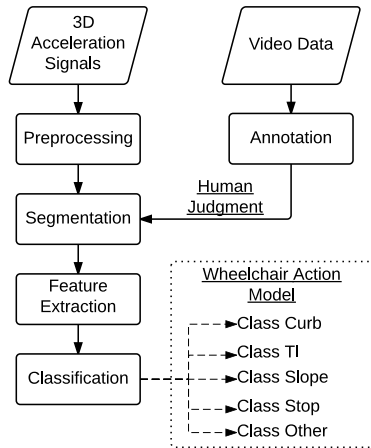


Fig. 5 Detailed flowchart of the modeling phase

Figure 5 is a detailed flowchart of the modeling phase. Similar to other human activity recognition processes, ground surface estimation consists of four processes, preprocessing, segmentation, feature extraction, and classification [31]. To evaluate the efficacy of acceleration data for ground surface estimation, we follow general procedures for every process. The predominant approach to activity recognition is based on a sliding window procedure, in which a fixed-length analysis window is shifted along the signal sequence for frame extraction.

For estimating target, we selected five wheelchair activities as indications of the accessibility where the wheelchair drove on: curb climbing, driving on tactile indicators, driving on slopes, driving on flat pavements, and stopping. The first three actions directly indicate the existence of an uncomfortable environment. Although such a physical barriers on ground surfaces have been recognized one of the causes of wheelchair accidents and incidents, information on risky or difficult sites have not easily been digitized and consequently remained unavailable. The stopping action is an example of a human action that interferes with road accessibility. For example, frequent stopping by wheelchair users might indicate danger. Videos were used for data annotation regarding terrain condition. Every frame of a video was categorized into one of five classes according to the ground surface on which the wheelchairs drove, and on whether the wheelchairs moved or was stationary: 1) climbing up curbs between a roadway and a sidewalk (class Curb), 2) moving on tactile indicators (class TI), 3) moving on slopes (class Slope), 4) stopping (class Stop), and 5) others (class Others). Note that, though the route includes other type of a physical barriers, such as section with rough pavement (Fig. 3 (g)), in this paper we didn't estimate them because they are rare and hard to annotated with the video data.

## 4. Evaluation

### 4.1 Evaluation Setup

We estimate accessibility information using general activity recognition procedures with a sliding window method and classifying feature vectors corresponding to fixed-size acceleration data. There are free parameters for classification, preprocessing, classifiers, segmentation window size, and feature extraction. Based on the results of preliminary experiments, we preprocessed the data with a moving average filter of length ten. Determining an optimal classifier is important for improving estimation accuracy. For the moment, we compare three classifiers that are widely used for action recognition tasks, support vector machine (SVM), random forest (RF), and k-nearest neighbor (KNN). Segmentation using a sliding window involves two parameters, window size  $w$  and overlap ratio  $p$ . Window size is the number of frames for each segment. Overlap ratio is the fraction of overlapping between  $S_{k-1}$  and  $S_k$ , assuming that  $S_k$  is the  $k$ -th segment. Although window size affects classification accuracy [32], the selection of a size is difficult and requires experimental evaluation. To find an optimal window, we tested different window sizes from 50 to 1,000 and investigated the relationships among the effects of window size.

Several studies have addressed the importance of designing appropriate sensor data feature representations [30], [33], [34], with no obvious winner yet. In this paper, based on activity recognition research [33], [34], we tested four features. The first is raw data (Raw Data), concatenating three sources of acceleration signals as  $[x_k^T, y_k^T, z_k^T]$ , where  $x_k$ ,  $y_k$ , and  $z_k$  are the vectors of  $k$ -th segment corresponding to each axis of acceleration signals respectively. Raw Data yields  $3w$ -dimensional representation of a segment, where  $w$  is a window size. The second (AveSTD) and third (Heuristic) are time-domain features. Time-domain features provide the basis for the most common approach to feature extraction in human activity recognition research. Given  $3w$  ( $w \times 3$ ) provided by the segmentation procedures, AveSTD calculates the mean and standard deviation for each source channel. This yields a six-dimensional time-domain representation of a segment. In addition, given the length of  $3w$  sensor data, Heuristic first calculates the difference sequences of each source channel,  $x_{kd}$ ,  $y_{kd}$ ,  $z_{kd}$ . Subsequently, we calculated the mean, standard deviation, maximum, and minimum for each source channel (i.e.,  $x_k$ ,  $y_k$ ,  $z_k$ ,  $x_{kd}$ ,  $y_{kd}$ ,  $z_{kd}$ ). The last feature is the frequency domain feature (Fd). The difference sequences emphasize high frequency component; the feature is expected to well capture the high frequently changes in acceleration signals by rough terrains. Fd converts the data into the coefficients of a fast Fourier transform (FFT) by applying FFT for each channel.



## 4.2 Classification Result

### 4.2.1 Overall

The first experiment was devoted to evaluation of classification performance when using particular feature extractors. Figure 6 shows the relationships between F-score and feature extractors for each classification task. In the all of below experiments, the classifications were conducted for each of four tasks Curb vs. Other, TI vs. Other, Slope vs. Other, and Stop vs. Other, for each participant individually. We have not conducted multi-class classification because it is a multi-label classification task, i.e., some segments are labeled as both Curb and TI, or another combination. The F-score of each classification was the average for nine participants, and F-score of each participant was calculated by general 10-fold cross validation procedures. Window size was set to 400 samples without overlapping, and the classifier was an SVM with a radial basis function (RBF) kernel.

On average, the F-score of Raw Data, AveSTD, Heuristic and FFT were 0.35, 0.64, 0.67, and 0.60, respectively. The best feature extractor was Heuristic, which estimated four actions with the F-scores (ranks) of 0.63 (1), 0.65 (1), 0.50 (2), and 0.91(3), respectively. The worst feature extractor was Raw Data, which estimated four actions with the F-scores (ranks) of 0.25 (4), 0.31 (4), 0.00 (4), and 0.87(4), respectively. Especially for the Curb and TI classifications, Heuristic highly exceeds other features. The results seem natural because difference sequences emphasize high frequency component and both actions require capturing high frequency changes of acceleration signals caused by sudden shaking. Another important point is that the Heuristic did not work well for all every cases, and slightly decreased the performance on recognition of long term actions Stop and Slope. These results suggest that using feature extractors suitable for each classification target is important to improve classification performance in the operations.

Figure 7 is a comparison between the F-scores of three classifiers, SVC, RF, and KNN when using the Heuristic feature extractor. The x-axis indicates the estimation target, and the y-axis indicates the F-score differences on the basis of the SVM classifier. The results indicate that in most cases, SVC outperforms the others. The least effective classifier is KNN, with a difference of  $-0.08$  on average. Both SVM and RF take the importance of features into account for classification, but KNN does not; this suggests that the features are not equally important. For improving the classification accuracy, feature selection might be of use.

The second set of experiments addressed the label data collection problem. For supervised classification, the annotation step incurs a cost for human judgment. We evaluated classification accuracies that can be achieved when the training sets used for estimating are limited artificially. Figure 8 shows the relationship between F-score and number of training data. The x- and y-axes indicate fractions of the original dataset and relative changes in F-score, respectively. As

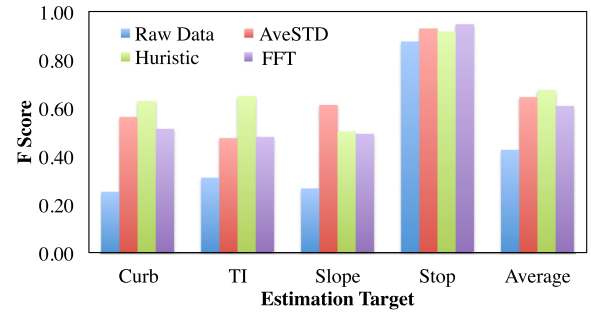


Fig. 6 Relationships among F-score, estimation targets, and features

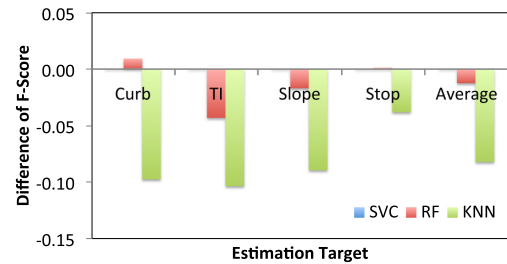


Fig. 7 Comparison of classifiers

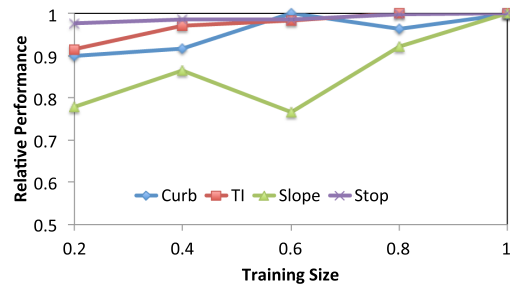


Fig. 8 Experimental evaluation of labeled data collection problem

a result, except for the Slope classification, sample size did not affect classification accuracy significantly. In the total of nine participants, the number of samples of Curb, TI, Slope, and Stop were 326, 661, 145, and 648, respectively; hence, the system maintains its estimation performance even with only 8, 15, or 3 samples for combinations of users and estimation targets.

### 4.2.2 Parameter Sensitivity

We evaluated the sensitivity of window size  $w$  and overlap ratio  $p$  of segmentations. Figure 9 shows the relationships between F-score and window size. The x-axis indicates window size ranging from 50 to 1,000 with steps of 50, and the y-axis indicates F-score. The general trend shows that the F-score of Curb and TI improves steadily and that of Stop worsens throughout. The fact that the F-score improves as the window size expands, even though the duration of the Curb action was approximately 1.0 s (50 samples), is of interest. As the larger window size leads to a window containing the overall pattern of action without splitting it into two

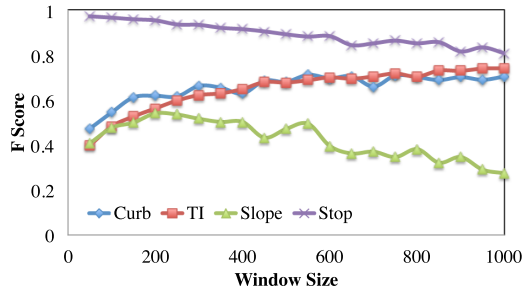


Fig. 9 Influence of window size  $w$  on F-score

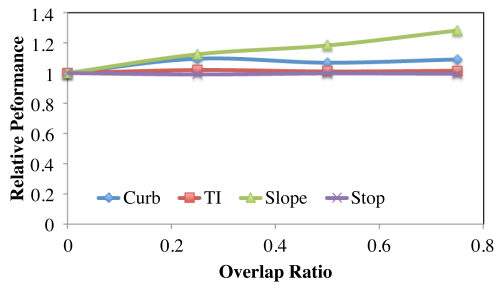


Fig. 10 Influence of overlap ratio  $p$  on F-score

windows, the results might imply that the overall pattern is required for detection of the actions of climbing and moving on tactile indicators.

In contrast to the above three actions, the trend of slope classification had an obvious maximum point at 200 samples. Figure 10 shows the relationships between F-score and overlap ratio. The x-axis indicates overlap ratio  $p$  between 0.0 and 0.75 with a 0.25 step size, and y-axis indicates relative change in the F-score on the basis of  $p = 0$ . As shown in Fig. 10, the relative change in the F-score of Slope was 1.28 instead of the result of other classifications. The larger window yields a smaller number of samples, and the larger overlap ratio yields a larger number of samples. Further investigation of this result is necessary, but both results suggest that the slope classification requires more samples to improve classification performance.

#### 4.2.3 Geo-Mapping Evaluation

Figure 11 shows a web mapping of estimated curbs (red), tactile indicators (yellow), and slopes (green) and a comparison with a mapping of correct actions. Window size was 400 without overlapping, the feature extractor was Heuristic, and the classifier was SVM for temporal evaluation. In total, 1,414 estimated data results from 27 laps (9 users times 3 laps) were simply mapped using Google Maps API v3. The rough tendency of roads was captured through visualization, even though tactile indicators were regarded as less accurate. The visualization was performed simply by mapping all 1,414 estimated results of data from 27 laps; hence, there is a great potential to improve visualization by using long-period data and statistical methods that consider multi-time estimations. Further work is required to address

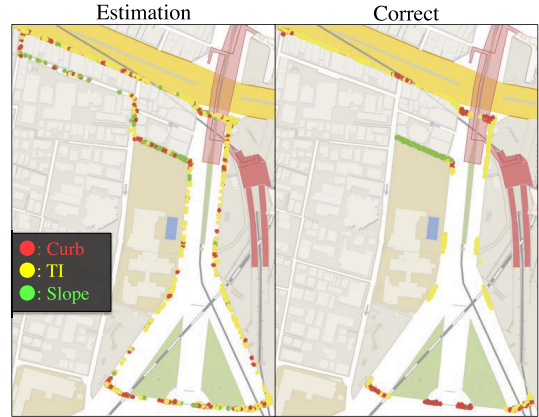


Fig. 11 Visualization of estimated results of 27 laps. Ground surfaces were mapped as red (Curb), yellow (TI), and green (Slope).

these issues.

## 5. Discussion

The experimental results show that the system with iPod touch attached to below the sheet of wheelchairs and machine learning is capable of detecting useful actions that indicates accessibility of roads: curb climbing, moving on tactile indicators, moving on slopes, and stopping. Though the question “which are the optimal features a what is the optimal classifier for the wheelchair datasets?” requires more comprehensive experiments using large-scale datasets, the experimental results here showed that the SVM and Random Forest that accommodate the importance of features were comparatively superior to K-NN. As for feature design, the heuristically-designed features (Heuristic) lead to a better performance for detecting actions when compared to other features, capturing high frequency changes in acceleration such as the ones appearing in “rough terrains”, i.e. those with curbing stones or tactile indicators. However, it harmed the classification performance when the estimation target is long-term. These results implied that we required to design appropriate features suitable for each classification targets or to develop sophisticated algorithms that adaptively extract the appropriate feature representations for each task.

At the end of this paper, we describe future directions considering the limitations of the prototype system, the evaluation results, and related work. We summarize future directions from the perspective of feasibility and extensibility.

### 5.1 Feasibility

This paper shows that the prototype system had the ability to visualize at least rough trends of the ground surface. The system is based on supervised machine learning; therefore, obtaining annotation data will become a bottleneck. Although the result shows that the system requires few annotation data, it is better if we reduce the training data further. One possible solution is to create a model that is useful for most users: impersonal model. In general, interclass va-

riety arising from differences among users is recognized as one of the major problems for developing such a model [31], and how to handle that issue is a further research question. The most straightforward solution is to develop a large-scale action database. Kawaguchi et al. proposed the concept of gathering a human activity corpus for real-world activity understanding [35]. A large-scale activity corpus is important not only for developing a personal estimation model but also for understanding impersonal characteristics. Once such characteristics are found, we can develop an impersonal model that can be applied for every user. A more sophisticated solution is to model the differences in actions between users using machine learning. Recent experiments on audio recognition tasks affected by speaker differences show that deep [36], helps in developing an impersonal speech recognition model [37].

Another constraint of the prototype system is sensor location. An iPod touch was attached below the sheet of a wheelchair in our system, but we would like to retain estimation performance regardless of sensor location, including users' pockets. Approaches for dealing with variations in device placement include 1) using robust features, 2) combining models specifically to detect device location, and 3) applying a transformation matrix as preprocessing [38].

## 5.2 Extensibility

The other limitation of the prototype system is that we estimate only general and rough-grained actions of wheelchair users, climbing up curbs, moving on tactile indicators, moving on slopes, stopping, and others. Accessibility visualization in cases in which wheelchair users take rare actions, such as falling or collision with pedestrians, is also of value, as is fine-grained action recognition as an indication of how dangerous or uncomfortable a site is. For example, whether a user handled the wheelchair effectively after climbing up bumps provides an indication of whether he or she felt in danger, and detecting such subtle differences in how the wheelchair was handled is important in evaluating the dangerousness of a bump. Addressing these issues requires modeling wheelchair driving actions and detecting rare actions using anomaly detection technologies [39], obtaining fine-grained features of sensor data by applying representation learning, such as that described in [34], and developing a large-scale action database.

## 6. Conclusion

This paper proposed a novel approach to accessibility data collection and visualization benefiting from recent expansion in human action sensing using smart devices and action recognition through machine learning. The strength of the proposed method is its low-cost data collection, a key to overcoming the problem that accessibility maps currently apply only to limited areas. We developed a prototype system that uses acceleration data of nine wheelchair users and supervised machine learning, and we evaluated the effi-

ciency of the methodology qualitatively and quantitatively. We found that the system detects curb climbing, moving on tactile indicators, moving on slopes, and stopping, with F-scores of 0.63, 0.65, 0.50, and 0.91, respectively. Mapping results of curb climbing, moving on tactile indicators, and moving on slopes showed that rough trends of maps can be captured using our methodology. Future work will be concerned with extending the estimation target for mapping rich accessibility information and reducing the constraints of the prototype system.

## Acknowledgements

We are deeply grateful to all participants of experiments, Dr. Fukushima, Mr. H. Uematsu, and Mr. Y. Uematsu. This study was supported by JPSP KAKENHI Grant Number 26-5331 and Tateishi Science and Technology Foundation in FY 2011–12, "Personal Sensing Technologies for Road Surface Survey toward Comfortable Wheelchair Driving."

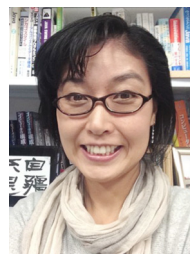
## References

- [1] Y. He, Y. Li, and S.-D. Bao, "Fall detection by built-in tri-accelerometer of smartphone," *Biomedical and Health Informatics (BHI)*, 2012 IEEE-EMBS International Conference on, pp.184–187, IEEE, 2012.
- [2] Y.-J. Hong, I.-J. Kim, S.C. Ahn, and H.-G. Kim, "Activity recognition using wearable sensors for elder care," *Future Generation Communication and Networking*, 2008. FGCN'08. Second International Conference on, pp.302–305, IEEE, 2008.
- [3] Y.-J. Hong, I.-J. Kim, S.C. Ahn, and H.-G. Kim, "Mobile health monitoring system based on activity recognition using accelerometer," *Simulation Modelling Practice and Theory*, vol.18, no.4, pp.446–455, 2010.
- [4] P. Wu, H.-K. Peng, J. Zhu, and Y. Zhang, "Senscare: Semi-automatic activity summarization system for elderly care," in *Mobile Computing, Applications, and Services*, vol.95, pp.1–19, Springer, Berlin, Heidelberg, 2012.
- [5] M.N.K. Boulos, S. Wheeler, C. Tavares, and R. Jones, "How smartphones are changing the face of mobile and participatory healthcare: an overview, with example from eCAALYX," *BioMedical Engineering OnLine*, vol.10, no.1, p.24, 2011.
- [6] M. Laakso, T. Sarjakoski, and L.T. Sarjakoski, "Improving accessibility information in pedestrian maps and databases," *Cartographica: The International Journal for Geographic Information and Geovisualization*, vol.46, no.2, pp.101–108, 2011.
- [7] N.D. Lane, M. Mohammad, M. Lin, X. Yang, H. Lu, S. Ali, A. Doryab, E. Berke, T. Choudhury, and A. Campbell, "Bewell: A smartphone application to monitor, model and promote wellbeing," *5th international ICST conference on pervasive computing technologies for healthcare*, pp.23–26, Citeseer, 2011.
- [8] D.W. Kang, J.S. Choi, J.W. Lee, S.C. Chung, S.J. Park, and G.R. Tack, "Real-time elderly activity monitoring system based on a tri-axial accelerometer," *Disability & Rehabilitation: Assistive Technology*, vol.5, no.4, pp.247–253, 2010.
- [9] R.S. Michalski, J.G. Carbonell, and T.M. Mitchell, *Machine learning: An artificial intelligence approach*, Springer Science & Business Media, 2013.
- [10] "World health organisation: International classification of functioning, disability and health," June 2015.
- [11] E.S. Bocato, E.R. Zorzal, and V. de Almeida, "Augmented reality as an accessibility tool for wheelchair users," 2012.
- [12] H. Matthews, L. Beale, P. Picton, and D. Briggs, "Modelling access

- with GIS in urban systems (MAGUS): capturing the experiences of wheelchair users," vol.35, no.1, pp.34–45, 2003.
- [13] H.A. Karimi, L. Zhang, and J.G. Benner, "Personalized accessibility map (PAM): a novel assisted wayfinding approach for people with disabilities," dx.doi.org, vol.20, no.2, pp.99–108, April 2014.
- [14] M.M. DiGiovine, R.A. Cooper, M.L. Boninger, B.M. Lawrence, D.P. VanSickle, and A.J. Rentschler, "User assessment of manual wheelchair ride comfort and ergonomics," *Archives of Physical Medicine and Rehabilitation*, vol.81, no.4, pp.490–494, April 2000.
- [15] C. Ponsard and V. Snoeck, "Objective accessibility assessment of public infrastructures," *Computers Helping People with Special Needs*, vol.4061, pp.314–321, Springer, 2006.
- [16] H.A. Karimi, *Advanced location-based technologies and services*, CRC Press, 2013.
- [17] C. Heipke, "Crowdsourcing geospatial data," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol.65, no.6, pp.550–557, 2010.
- [18] J. Howe, "The rise of crowdsourcing," *Wired Magazine*, vol.14, no.6, pp.1–4, 2006.
- [19] C. Cardonha, D. Gallo, P. Avegliano, R. Herrmann, F. Koch, and S. Borger, "A crowdsourcing platform for the construction of accessibility maps," *Proceedings of the 10th International Cross-Disciplinary Conference on Web Accessibility*, p.26, ACM, 2013.
- [20] T. Miura, K.-I. Yabu, S. Ikematsu, A. Kano, M. Ueda, J. Suzuki, M. Sakajiri, and T. Ifukube, "Barrier-free walk: A social sharing platform of barrier-free information for sensory/physically-impaired and aged people," pp.2927–2932, 2012.
- [21] K. Shigeno, S. Borger, D. Gallo, R. Herrmann, M. Molinaro, C. Cardonha, F. Koch, and P. Avegliano, "Citizen sensing for collaborative construction of accessibility maps," *Proceedings of the 10th International Cross-Disciplinary Conference on Web Accessibility, W4A '13*, New York, NY, USA, pp.24:1–24:2, ACM, 2013.
- [22] K. Hara, V. Le, and J. Froehlich, "Combining crowdsourcing and google street view to identify street-level accessibility problems," pp.631–640, 2013.
- [23] K. Hara, "Scalable methods to collect and visualize sidewalk accessibility data for people with mobility impairments," *Proceedings of the adjunct publication of the 27th annual ACM symposium on User interface software and technology*, pp.1–4, ACM, 2014.
- [24] M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," *Neurocomputing*, vol.100, pp.144–152, Jan. 2013.
- [25] X. Yang, A. Dinh, and L. Chen, "Implementation of a wearable real-time system for physical activity recognition based on naive bayes classifier," *Bioinformatics and Biomedical Technology (ICBBT), 2010 International Conference on*, pp.101–105, IEEE, 2010.
- [26] D.W. Kang, J.S. Choi, J.W. Lee, S.C. Chung, S.J. Park, and G.R. Tack, "Real-time elderly activity monitoring system based on a tri-axial accelerometer," dx.doi.org, vol.5, no.4, pp.247–253, June 2010.
- [27] A. Pantelopoulous and N.G. Bourbakis, "A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis," *Systems, Man, and Cybernetics, Part C: Applications and Reviews*, IEEE Transactions on, vol.40, no.1, pp.1–12, Jan. 2010.
- [28] C. Prandi, P. Salomoni, and S. Mirri, "mPASS: Integrating people sensing and crowdsourcing to map urban accessibility," *Proceedings of the IEEE International Conference on Consumer Communications and Networking Conference*, pp.591–595, 2014.
- [29] Y. Fukushima, H. Uematsu, R. Mitsuhashi, H. Suzuki, and I.E. Yairi, "Sensing human movement of mobility and visually impaired people," *The proceedings of the 13th international ACM SIGACCESS conference on Computers and accessibility*, pp.279–280, ACM, 2011.
- [30] O.D. Lara and M.A. Labrador, "A survey on human activity recognition using wearable sensors," *Communications Surveys & Tutorials*, IEEE, vol.15, no.3, pp.1192–1209, 2013.
- [31] A. Bulling, U. Blanke, and B. Schiele, "A tutorial on human activity recognition using body-worn inertial sensors," *ACM Computing Surveys (CSUR)*, vol.46, no.3, p.33, 2014.
- [32] O. Banos, J.-M. Galvez, M. Damas, H. Pomares, and I. Rojas, "Window size impact in human activity recognition," *Sensors*, vol.14, no.4, pp.6474–6499, 2014.
- [33] D. Figo, P.C. Diniz, D.R. Ferreira, and J.M.P. Cardoso, "Preprocessing techniques for context recognition from accelerometer data," *Personal and Ubiquitous Computing*, vol.14, no.7, pp.645–662, 2010.
- [34] T. Plötz, N.Y. Hammerla, and P. Olivier, "Feature learning for activity recognition in ubiquitous computing," *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, p.1729, 2011.
- [35] N. Kawaguchi, N. Ogawa, Y. Iwasaki, K. Kaji, T. Terada, K. Murao, S. Inoue, Y. Kawahara, Y. Sumi, and N. Nishio, "Hasc challenge: gathering large scale human activity corpus for the real-world activity understandings," *Proceedings of the 2nd Augmented Human International Conference*, p.27, ACM, 2011.
- [36] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *Pattern Analysis and Machine Intelligence*, IEEE Transactions on, vol.35, no.8, pp.1798–1828, 2013.
- [37] L. Deng, G. Hinton, and B. Kingsbury, "New types of deep neural network learning for speech recognition and related applications: An overview," *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*, pp.8599–8603, IEEE, 2013.
- [38] A. Henpraserttae, S. Thiemjarus, and S. Marukatat, "Accurate activity recognition using a mobile phone regardless of device orientation and location," *Body Sensor Networks (BSN), 2011 International Conference on*, pp.41–46, IEEE, 2011.
- [39] J.L.C. Candás, V. Peláez, G. López, M.Á. Fernández, E. Álvarez, and G. Díaz, "An automatic data mining method to detect abnormal human behaviour using physical activity measurements," *Pervasive and Mobile Computing*, vol.15, pp.228–241, 2014.



**Yusuke Iwasawa** is currently a Ph.D candidate at Tokyo University under the supervision of Dr. Yutaka Matsuo. He received his M.S. degree from Sophia University, Japan in Artificial Intelligent Application. He obtained his B.S. degree with computer engineering major from the faculty of information and science, Sophia University, Japan.



**Ikuko Eguchi Yairi** received B.S., M.S., and Ph.D. degree in mechanical engineering from University of Tokyo in 1994, 1996 and 1999, respectively. She previously worked at National Institute of Information and Communications Technology (NICT) from 1999 to 2008. She is currently an associate professor at Sophia University. Her interests are human factors in artificial intelligence, artificial intelligence for computer human interaction, and assistive technologies for impaired people.





**Yutaka Matsuo** received the B.S., M.S., and Ph.D degrees from the University of Tokyo in 1997, 1999, and 2002, respectively. He is an associate professor at the Institute of Engineering Innovation, The University of Tokyo, Japan. He joined National Institute of Advanced Industrial Science and Technology (AIST) from 2002 to 2007. He is interested in social network mining, text processing, and semantic web in the context of artificial intelligence research.