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Toward an Automatic Road Accessibility Information Collecting and Sharing Based on Human Behavior Sensing Technologies of Wheelchair Users

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Abstract

This research proposes a methodology for digitizing street level accessibility with human sensing of wheelchair users. The digitization of street level accessibility is essential to develop accessibility maps or to personalize a route considering accessibility. However, current digitization methodologies are not sufficient because it requires a lot of manpower and therefore money and time cost. The proposed method makes it possible to digitize the accessibility semi-automatically. In this research, a three-axis accelerometer embedded on iPod touch sensed actions of nine wheelchair users across the range of disabilities and aged groups, in Tokyo, approximately 9 hours. This paper reports out attempts to estimate both environmental factors: the status of street and subjective factors: driver's fatigue from human sensing data using machine learning.

Peer-review under responsibility of the Program Chairs

Keywords: Smart Device, Street-level Accessibility, User Fatigue, Human Behavior Sensing, Machine Learning

1. Introduction

Recent expansion of intelligent gadgets, such as smart phones and wristwatch shaped vital sensors, boost a good relationship between human behavior sensing in daily lives and useful applications in ubiquitous computing. We have been developing an automatic road accessibility information collecting system that was inspired by human behavior sensing technologies of wheelchair users[1]. Automatic road accessibility information collecting and sharing is important especially for people with mobility difficulties, e.g. visually disabled and wheelchair users, to secure their routes. Current road accessibility information collecting needs manpower that requires monetary assistance for professional accessibility advisers by local governments or unpaid works by volunteers. Road accessibility information sharing has been stagnated such as accessibility maps of station yards and campuses.

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The purpose of this research is to propose a breakthrough of the stagnation with human behavior sensing technologies of wheelchair users. Our proposed system estimates ”accessibility indicators” from sensor data that records daily actions of wheelchair users with smart phone to visualize street-level accessibility. Accessibility indicators are environments, events, and user contexts that show the status and/or the goodness of roads explicitly and implicitly. Typical example of environmental indicators are curbs and slopes and that of human factors is wheelchair users feeling tired. The system digitize these accessibility indicators, mapped it, and shared as web maps. These estimated results from human sensing data of wheelchair users who are moving on walkway, such as climbing curbs and muscular fatigues, might be regarded as less accurate than those that are collected by manpower. But an accumulation of these results for long periods helps to increase accuracy of the estimation results. The most important feature of our system is to estimate and visualize wheelchair users subjective data like muscular fatigues that are very difficult to collect by current method with manpower. Indication of the point where wheelchair users felt tired is useful to others, e.g. visually impaired people and pregnant women, because terrains which could be physical burdens for human mobility functions and could cause fatigues with no regard for means of moving, wheelchair or foot. Terrains on walkways are important factor for walkers and wheelchair users, thus it should be also estimated and visualized as environmental factors as well as human factors.

This paper reports our attempts of two estimations, estimation of environmental factors and human factors, from real wheelchair sensing data by accelerometers in iPod touch to develop autonomous street-level accessibility data collecting and sharing. Estimation of environmental factors is demonstrated as extraction of curbs, tactile blocks and slopes on walkways. Estimation of human factors are also done focusing on wheelchair users wheel pushing action for extracting muscular fatigue while moving. Contributions of this paper are summarized in two points. One is to propose a method of road accessibility information collecting and sharing with human behavior sensing technologies of wheelchair users, which are mentioned in next section being compared with related works. The other one is to evaluate our proposed method of road accessibility estimation with real sensing data of wheelchair users on walkways. These evaluations are described in the next part of this paper. The final part of this paper concludes the paper with future challenges.

2. Autonomous Accessibility Mapping

2.1. Estimation of Street-level Accessibility using Sensor Data

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. Fig. 1 shows an architecture of the proposed system. Our system visualizes street-level accessibility utilizing wheelchair sensing methodology. Basically, the system estimate accessibility indicators from sensing data that recorded by wheelchair attached acceleration sensors. Sensing and estimating human behaviors of wheelchairs with smart phone is one of the central parts of the system. Strength of utilizing the smart phone is that, users could use sensing application through Google Play Store or iTunes store without any extra hardware costs. Sensor analysis modules analyze the data, estimate accessibility information, and store the information on spatiotemporal database in an anonymous manner. Mapping module visualizes the information as web maps. The system enables users to check the accessibility of where they want to go and to select safer routes than others.

Both objective and subjective data are important to effectively visualize the street-level accessibility, and human sensing data of wheelchair users contains information. One of the typical objective information is the status of roads, such as curbs, gaps, and slopes (environmental factors). Estimation and visualization of these objective factors on web maps are useful for users to select comfortable route, and for the system to propose optimal route considering user’s preferences information for each obstacles. Subjective information, such as fatigues and uncomfortable of users are also important for every users because the place might also make another user tired. Also, digitizing and combining both objective and subjective information would be of interest to characterize what kind of factors cause fatigues and utilize the knowledge to improve city designs.

2.2. Related Work

Lots of research proposed accessibility data collection methods, but it all requires lots of manpower. Most classical and predominant data collection approach is official review, assessing the ground surfaces by experts. A new trend is geo-crowdsourcing, utilizing crowd of people for evaluating accessibility of roads through web site[2,3], and a lot of studies proposed systems using the geo-crowdsourcing[4,5,6,7]. Both methods could provide accurate information; however, it requires manpower, and therefore money and time costs. Instead, only requirements for our system is just installing a application on their smart phone, and estimation will be done by using machine powers. An advantage of our system is low-cost accessibility data collection benefitting recent development of human sensing with smart phone like sensors, and machine learning. Another advantage is system extensibility. Because human sensing data contains ideally entire life of users, various type of user information could be estimated. For example, the information about where user actually felt tired and/or where the accidents were happened are significantly important, but this information were hard to collect by official review and crowdsourcing. Generally, such subjective information is hidden state that could not observed directly, but it affects some observable variables such as actions. Our wheelchair sensing method gathers individual activities as sensor data, so there are plenty of probability to estimate even subjective information as change of behavior, emergence of abnormal behavior and so on.

Although many sensing apps, architectures, and algorithms have been proposed to recognize human behaviors from smart phones sensing data[8,9], and it may applicable to the accessibility extraction, as far as authors knows, application of wheelchair sensing on accessibility data collection weren't evaluated. Prandi et.al propose a concept combining three available sources, official review, crowdsourcing and sensing, and a useful architecture to achieve the concept[10]; however, they don't propose a methodology itself to estimate accessibility information. Fukushima and colleagues directly map vibration acceleration levels (VALs) that is a root mean average of three axis acceleration values, a_x, a_y, and a_z[11], and compared it with user activities. This paper shows estimation of the accessibility information from both objective and subjective viewpoints.

3. Evaluation Setup

In this paper, we demonstrate two estimations: ground surface estimation as estimation of environmental factors and driver's fatigue estimations as user context estimation. For evaluations, nine wheelchairs driving data were collected for experiments in Tokyo. Basically, the data are combination of 3-D acceleration signals, location information, and annotation data that was carefully made by human judgments. Fig. 2 shows the sensing system of experimental data collection. The iPod touches were attached to the right and left wheelchair tires, and under the sheet, and recorded his/her outdoor activities using 3-axis accelerometers mounted on them. A receiver of Quasi Zenith Satellites System (QZSS) was attached to the back of the wheelchair. Video camera recorded entire activities from back of the wheelchairs. The sampling rate of the accelerometer and video were 50Hz and 30Hz respectively.

Research participants were nine wheelchair users, seven male and two female, six manual wheelchair users and three powered wheelchair users, aged between 20s-60s. Each participant drove on two designated routes, three laps for route1 and one lap for route2 whose length were approximately 1.5 km both, and two collaborators ran parallel to the wheelchairs to ensure the safety of the experiments. The routes are designed to include typical Japanese routes, including curbs, sloping roads, and various type of surfaces. The driving time of each participant was approximately one hour for route1 and twenty minutes for route2. In order to keep the driving data natural as possible, we didnt limit his/her activities including driving speed and positioning on walkways.

4. Estimation of Environmental Factors: Ground Surface Estimation

4.1. Analysis Method

All of nine participants driving data of route1 were used for ground surface estimations. Fig. 3 shows a flowchart of the estimation procedure. The recorded 3-axis acceleration signals was preprocessed, and then segmented into fixed length frames. A feature extractor converted the frames into some type of feature vectors, and classifier estimated the ground surface conditions. Based on results of preliminary experiments, the window size was set to 400 samples

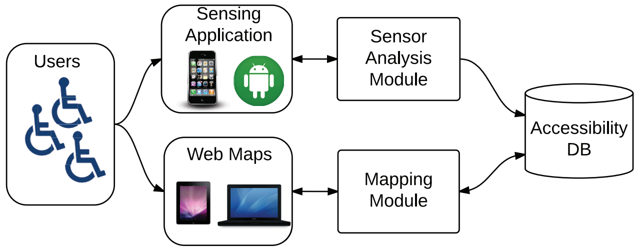

Fig. 1: Architecture of the proposed system

Fig. 2: Sensing System

(approximately 4.0 seconds) with fifty percent overlaps. Also, a moving average filter whose length is ten was used for prepossessing. An optimal classifier is one of the biggest interesting issues for improving estimation accuracy; however, this is beyond the scope of this paper, and will be mentioned another paper. For the moment, this paper used Support Vector Machine (SVM) as a classifier that is experimentally proved as one of the efficient supervised machine learning techniques in various domains. Popular Radial Basis Function (RBF) kernel was selected as kernel function. Parameters for SVM and RBF kernel were optimized by a grid search, between 10^{-12} and 10^{2} for the cost of SVM and between 10^{-6} and 10^{6} for gamma of the RBF kernel.

Several researches has addressed the importance of designing appropriate feature representation of sensor data [12,13,14]; however, there are no obvious winner yet. In this paper, we designed two feature vectors, 1) time domain feature (Ft) and 2) frequent domain feature (Ff). Time domain feature is the most common approach to feature extraction for this field. Given 1200 (400×3) provided by the segmentation procedures, we first calculated the difference sequences of each source channels, x_d, y_d, z_d. Subsequently, we calculated mean, standard deviation, maximum, and minimum for each source channels (i.e. x, y, z, x_d, y_d, z_d). This yields a 24-D time domain representation of a segment. Also, channel-wise Fourier analysis on the raw signal data calculated the frequent domain feature. This yields a 600-D frequent domain representation.

For classifications, the videos were used for data annotation about terrain existence. Every frames of videos were identified as following four classes according to the ground surface where the wheelchairs drove on: 1) curbs between a roadway and a sidewalk (class Curb), 2) tactile indicators (class TI), 3) slopes (class Slope), and 4) others (class Others). All three terrains are typically referring as uncomfortable or risky sites for wheelchair users. Note that the class balance was highly imbalanced. For example, approximately only 14 seconds data were correspond to the class Curb, in entire 60 minutes driving of a parson. Generally, learning from the imbalanced data is a difficult task [15]. We handled the problem by use cost sensitive learning methods [15] that use differences cost for each class so that the misclassification of positive minority samples influence worse for objective function of classifier than that of negative majority samples.

4.2. Estimation Result

Table 1 shows the result of classifications using the time domain features Ft. The classifications were conducted for each three task (Curb vs. Other, TI vs. Other, and Slope vs. Other), and each participant individually. We haven't conducted multi-class classification because it is multi label classification task, i.e. some samples are labeled as both curbs and TI, or any other combinations. The f1-score, recall ratio, and precision ratio of each classification were average of nine participants. As a result, the f1-scores were 0.61, 0.64, and 0.47 respectively for each task. Note that, even the 0.47 is much better than random choice because of the imbalances of samples. The classification accuracy were varied widely depend on the dataset (i.e. the parson). For example, the best f1-score for curb classification was 0.82 and the worst one was 0.47. One of the major causes was a wheelchair type. For example, f1-score of powered wheelchairs dataset was 0.72 for curb classification on average, and that of manual wheelchairs dataset was 0.56. Further investigation for the result is necessary, but possible explanation is that powered wheelchairs driving is more

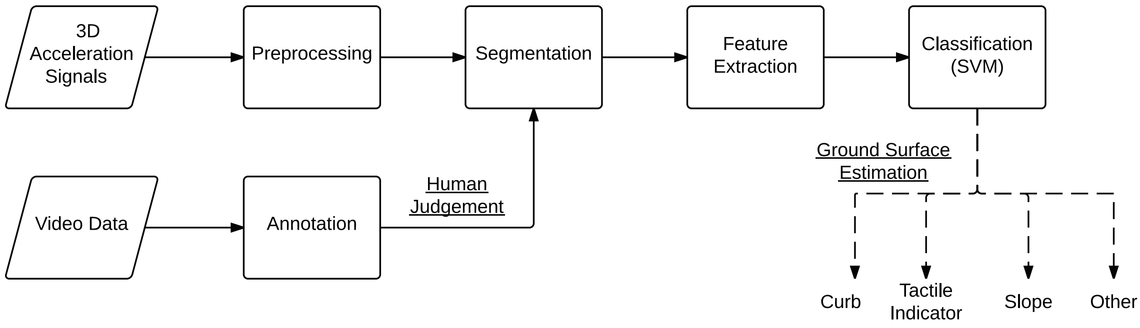

Fig. 3: A flowchart of the ground surface estimation

affected by the conditions of ground surfaces than that of manual wheelchair. Manual wheelchair users might be able to avoid impacts by driving techniques such as wheelies.

Fig. 4 shows a comparison of f1 scores between the time domain features and the frequent domain features. The f1 scores are average of nine participants. As a result, the time domain features marked comparatively good estimation performance for the curbs and the tactile indicators estimation. As for the slope estimation, results are similar to each other. In more details, within the all-27 combination of nine participants and three classification tasks, the time domain features were with twenty-two wins and five loses. To improve the accuracy, suitable features designs, and representation learning [16,17] might be helpful.

Table 1: Classification results with the time domain features

Targe	Total (Nine Datasets)			Powered (Three Datasets)			Manual (Six Datasets)		
	F1 Score	Precision	Recall	F1 Score	Precision	Recall	F1 Score	Precision	Recall
Curb	0.61	0.54	0.78	0.72	0.69	0.82	0.56	0.46	0.76
TI	0.64	0.58	0.75	0.63	0.57	0.74	0.65	0.58	0.76
Slope	0.47	0.45	0.57	0.66	0.66	0.68	0.37	0.35	0.51

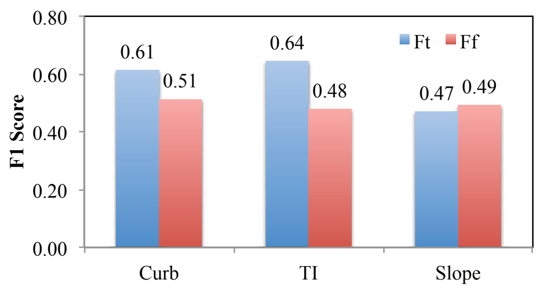

Fig. 4: Comparison of f1 scores of three classification between the time domain features and the frequent domain features

5. Estimation of User Factors: Driver's Fatigue Estimation

5.1. Analysis Method

Users's fatigue is practical information for judging the route is good or not. Estimation of such a user factors is difficult because it is generally unobservable from outside. However, user fatigue status might influence to users actions. The basic idea of this paper is to detect the change of observable status: action patterns, instead of estimation of hidden status: user fatigue itself. Especially, in this paper, we focus on wheelchairs pushing actions. 'Pushing' is typical actions for accelerating wheelchairs speed by following four sub-actions: grasping push rims beside wheels, pushing them for rolling wheels, and releasing their hands from push rims. The reasons why we focused on pushing actions are as follows: 1.) Pushing action is repeated on moving whether users feel tired or not, thus the sensing data comparison is reasonably applicable. 2.) Wheel pushing is one of the most susceptible actions to muscular fatigues. One pushing action is defined as showed in Fig. 5. Start of a pushing is when a user grasps a rim as a second part in Fig. 5, and finish of a pushing is when a user releases his/her hand from the rim as a fourth part in Fig. 5.

Fig. 6 show a flowchart of the analysis to find the characteristic patterns. To characterize the fatigue patterns, we created a pushing pattern dataset; the dataset consists 100 fatigue patterns and 100 non-fatigue patterns. The acceleration data with muscular fatigue (abbrev. the fatigue data) was sampled from the wheelchair sensing data before a falling accident. The acceleration data without muscular fatigue (abbrev. the non-fatigue data) was sampled from the same persons wheelchair sensing data at the beginning of his driving experiment. The reason why we extracted fatigue pattern just before falling accident is that the accident probably be caused by muscular fatigue after 5km driving. His escort had recognized his fatigue and asked him to halt his driving experiment before this falling. For more detail, one hundreds fatigue patterns are extracted from the fatigue data for 190 seconds just before falling, and 100 non-fatigue patterns are extracted from the non-fatigue data for 150 seconds at early parts of the sensing experiment.

This paper show the characteristics of fatigue-pushing by taking following three steps: 1) finding typical pushing patterns by clustering method, 2) naming it by the ratio of samples, and 3) comparing fatigue typical patterns and non-fatigue typical patterns. At first, all 200 samples were clustered into some clusters based on the similarity of acceleration patterns. Naming each typical pattern as either 'fatigue' or 'non-fatigue' based on a simple threshold, we compared 'fatigue' and 'non-fatigue' pushing. We applied K-means, which is a well-known non-hierarchical clustering method, to the dataset. Data length of each samples was different because time duration of pushing is

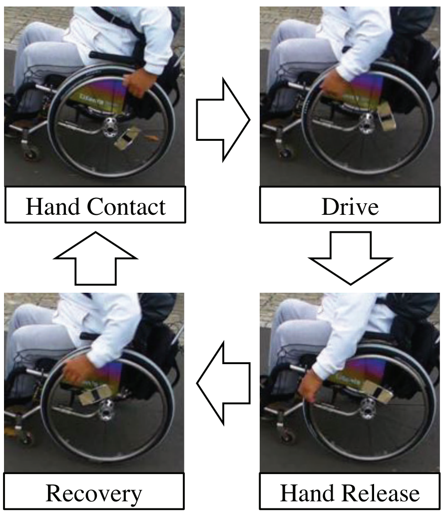

Fig. 5: Definition of pushing action duration

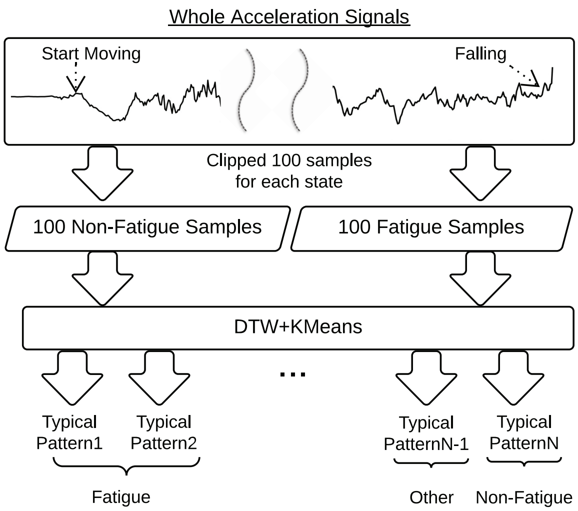

Fig. 6: A flowchart of the analysis of the fatigue analysis

different. Dynamic Time Warping (DTW)[18] was used as distance metric to treat difference of data length. Silhouette Score was also adopted as an indicator to decide the number of the cluster[19]. Considering scores of 2 to 20 clusters, the score of 5 clusters was selected.

5.2. Estimation Result

Fig. 7 shows a timeline chart of the clustering results. Blackened blocks located at (cluster i, k) represents the kth pushing belongs to the cluster i. The top chart represents transitions of pushing on the non-fatigue data (abbrev. non-fatigue pushing), and the bottom one represents that of pushing on the fatigue data (abbrev. fatigue pushing). The charts show that most non-fatigue pushing belonged to cluster1, and most fatigue pushing belonged to cluster 0. Also, except the cluster2, the cluster members were highly biased for either the fatigue pushing or the non-fatigue pushing. The two results indicate that there are clear differences between the fatigue pushing and non-fatigue pushing, which is measurable with the simple DTW metrics.

Fig. 8 shows representative acceleration patterns of each cluster. The vertical axis is for the acceleration values ranged between -0.3 G to 0.2 G, and the horizontal for time. At the first glance, there might be three groups in representative patterns. The first group members are cluster0 and cluster 3, whose patterns represent the fatigue pattern, and are characterized by decrease pattern at the beginning of a pushing and increase pattern at the end. The second group members are cluster2 and cluster4, whose patterns represent the non-fatigue pattern, and are characterized by the increase pattern from the beginning to the end of a pushing. The third group member is cluster 1, whose patterns represents the non-fatigue pattern and is characterized by middle state of first and second groups. A possible explanation of the differences between these three groups is that touching tire rims for pushing wheels could be obstructive to wheel acceleration, and cause the decrease pattern at beginning on the pushing of cluster0 and cluster 3. The cluster2 and the cluster4 show incremental patterns, because there might be the non-obstructive pushing without fatigue. The patterns of cluster1 might be little-obstructive pushing.

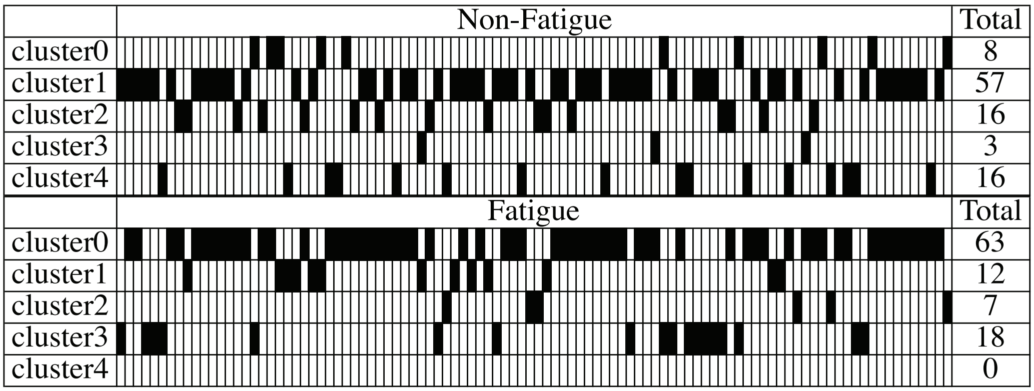

Fig. 7: Timeline charts of each cluster

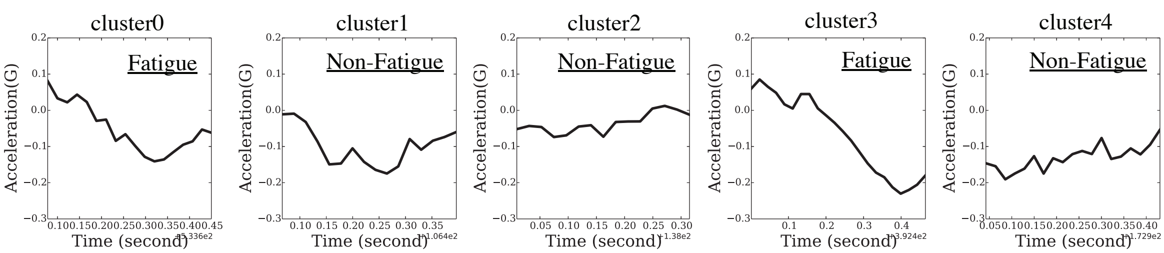

Fig. 8: Comparison of pushing patterns of each cluster

6. Conclusion

This paper proposed a novel application of wheelchair behavior sensing with smart devices on accessibility data collection. The driving data of nine wheelchair users were carefully collected in natural outdoor environments for approximately 10.8 hour with 3-D accelerometers. We tested the capability of smart phone sensing for ground surface estimations and a wheelchair users fatigue estimation. Experimental results show that our method had capability of estimating the curbs between a roadway and a sidewalk, the tactile indicators, and the slopes with 0.61, 0.64, 0.49 f1-score respectively. Also, tracking the pushing activity was effective for the fatigue estimation. These findings are significant toward developing autonomous accessibility mapping and helping human with the disabilities of mobility. The next s.pdf would be following three things: 1) Developing model that is capable of handling new users, 2) Proposing more accurate classification procedures for wheelchair activity recognition, and 3) Developing accessibility visualizing method that consider massive and variety data including ground surface conditions and drivers fatigue state.

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