Life-Logging of Wheelchair Driving on Web Maps for Visualizing Potential Accidents and Incidents

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Abstract. Life-logging has attracted rising attention as the most fundamental elements for developing every rich software today. This paper presents computational estimation and mapping of potential accidents and incidents of wheelchairs from life-logs with a single cheap and mini-sized three-axis accelerometer mounted on a wheelchair. Wheelchair driving data was obtained by real wheelchair users driving with their wheelchair on real roads, but has the sampling time delay and noises. As a first step of computational estimation, wheelchair driving behavior was classified into moving and static action, and the moving action was divided into tough and smooth status of the ground surface. We employed Support Vector Machine for classification, and made the precise supervised data from the video of wheelchair driving. As the result of classification, estimation of moving/static was achieved 98.2% accuracy rate and estimation of tough/smooth surface was achieved 82.6% accuracy rate. From the surface estimation result, wheelchair-driving difficulty was mapped and evaluated.

Keywords: Life-Log, SVM, time-series classification, wheelchair.

1 Introduction

Recently life-loggers no longer wear heavy computers and large devices in order to capture their entire lives, or large portions of their lives. In accordance with the expanding smartphone sales, life-logging has become popular application and attracted rising attention as the most fundamental elements for developing every rich software, from the end-user applications to the big data management tools in the era of ubiquitous and cloud computing. So we have been developing life-logging application of wheelchair users[1].

This paper introduces our approach to the time series data analysis of wheelchair user's life-log on driving with three-axis accelerometers. Three-axis accelerometers are mounted on most recent popular smart phones, and their time-series data includes useful human behavior patterns. If wheelchair users sense and

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record their driving behavior with three-axis accelerometers as life-logs, their motion such as stopping, moving and near-falling accidents, and the status of the ground surfaces such as smooth and bumpy will be estimated from time-series patterns of three-axis accelerometers. The human behavior information where near-falling accidents occurred is very important for all wheelchair users to prevent accidents on driving. The information of the environment surrounding wheelchairs such as where bumpy roads are is also necessary for them to choose maneuverable routes on driving. Of course, simple trails of wheelchairs are practical information for wheelchair users as the evidential fact where wheelchairs were able to access. But a simple trail provides no information about whether a user took a lot of trouble on driving on the route or not. The information about this driving difficulty can be extracted by the estimation of human behavior and environmental information from wheelchair driving logs with time-series data of accelerometers. If wheelchair trails and the extracted information from driving logs such as near-falling accidents and bumpy roads are mapped on web maps, essential support will be provided to expand the mobility of each wheelchair user.

We would like to classify time-series of acceleration values into some driving action patterns for estimating and visualizing the information about driving difficulty in this paper. Although there are some application to evaluate the ground surface condition [2][3], these application have focused on improving the wheelchair driving environment, it is not enough to visualize the information about human action. In order to estimate a information about driving difficulty for a wheelchair user from life-logs, classifying action pattern is necessary as conducting at a research which purpose to achieve the health management system fitting for individuals from human behavior 'life-log'[4][5]. There are a few studies which focus on classifying wheelchair driving behavior. However, these studies have only dealt with the data of non-handicapped person [6], so classification using wheelchair users data at moving on actual environment have not been discussed. Our approach to classify and visualize the mobility barrier is different with another studies in terms of using wheelchair users driving data and classifying it, and novelty.

According to Zhengzheng's survey [7], sequence classification can be classified into three main groups, 'Feature Based Classification', 'Sequence Distance Based Classification' such as K nearest neighbor classifier(KNN) or SVM, and 'Model Based Classification' such as Hidden Markov Model(HMM). Especially, regarding time series data like acceleration values, 'Sequence Distance Based Classification' are widely adopted to classify. We adopt SVM to classify time series of acceleration values into driving actions. Recently, SVM has proved to be an effective method and some studies use SVM for sequence classification [8][9][10][11]. Before to make clear what kind of classification method is optimal and how is its accuracy with wheelchair driving data, this paper focuses on the SVM as an ordinary classification method to precisely analyze the obtained wheelchair driving data on the experiments.

In this paper, we introduce our collected data of wheelchair driving by real users and our first step analysis of the data with SVM for the estimation of the human behavior and the status of the ground surface. The collected data is not clean because of sampling time delay and is noisy, containing outlier. The estimation from the data may require some creative algorithm which is optimum for the data characteristics. However, we never mentioned about an optimum algorithm in this paper. Our purpose is to clarify the characteristics of our collected data of wheelchair driving from the classification analysis using SVM. The remainder of this paper is organized as follows. The classification analysis framework is proposed in Section 2. A classification tree to digitize and visualize the potential accidents and incidents is discussed. Section 3 is devoted to a brief introduction to the collected data on wheelchair driving experiments and our employed classification method for data analysis. Results of the data analysis are presented in Section 4. The conclusion and future works are showed in Section 5.

2 Visualization of Potential Accidents and Incidents of Wheelchairs Driving

Typical serious accidents of wheelchairs were reported, for examples, as follows: wheelchair falls because of sidewalk curbs, collision accidents of wheelchairs because of loss of control at long or steep slopes, and car accidents with wheelchairs which were reluctantly moving on driving road to avoid uneven sidewalks. There is no question that these accidents were caused by the physical barriers to wheelchair mobility on the ground surface such as roughness and terrains. Behind these serious accidents, the physical barriers on the ground surface also cause so many incidents, as non-injury accidents [12][13][14].

Wheelchair users can not access the information where these accidents and incidents tend to occur because these information are difficult to digitize without manpower and special skills in wheelchair mobility barrier assessment. So each wheelchair user faces a daily challenge to manipulate his/her wheelchair on the ground surface with undiscovered dangers. These challenges under undiscovered dangers lead to the mental and physical stress for wheelchair users on outdoor activities. To lessen the mental and physical stress of wheelchair users, it is indispensable to digitize the information about physical barriers for wheelchair mobility on the ground surface and to visualize the possibility where accidents and incidents tend to occur. To digitize and visualize this information is a important mobility support method which enables wheelchair users to judge the risk of driving on a certain route in advance and to plan a safer route.

As a first step of digitization and visualization of mobility barriers of wheelchairs on the ground surface, we attached single three-axis accelerometer to wheelchairs of seven mobility-disabled persons, and collected the driving data on several routes in Akihabara area. The data was mapped and color-coded according to the Vibration Acceleration Level (abbr. VAL). But this color-coded VAL map shows little information of the ground surface about accidents and incidents risk. Because the simple acceleration value indicates the degree of vibration which a wheelchair user felt on driving and which was influenced by a wheelchair user's driving such as speed, sudden starting and stopping, and so on. Required solution for wheelchair users' needs is not mapping the degree of vibration from acceleration value on web, but mapping the ground surface conditions which are estimated from time series of acceleration values with machine learning techniques.

Consequently, this paper proposes the estimation of mobility barriers on the ground surface from time series of acceleration values on wheelchair driving with machine learning techniques. To clarify the estimation objectives, we describe wheelchair driving behavior as the classification model shown in Figure 1. As the first level classification, wheelchair-driving behavior is divided into moving and static actions. As the second level classification, moving action is divided into moving on the ground surface with/without mobility barriers. Through this two step classification, this paper investigates the possibility of the estimation of mobility barriers on the ground surface from time series of acceleration values on wheelchair driving with machine learning techniques.

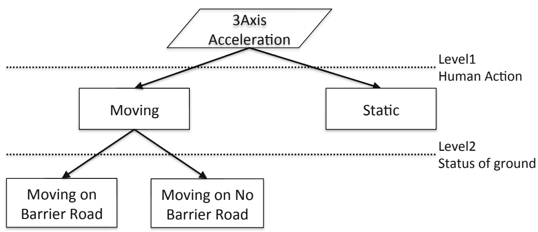


Fig. 1. The classification model of wheelchair driving behavior

3 Estimation of Mobility Barriers on the Ground Surface from Life-Log

3.1 Wheelchair Diving Data

Seven mobility disabled persons participated in wheelchair driving experiments of our laboratory and then wheelchair driving movement data was measured by a Sun SPOT, three-axis accelerometers attached under the wheelchair seat, as figure 2. Sun SPOT is cheap like smartphone and is easier to attach to the narrow space under the wheelchair. In order to obtain natural driving data, each person was asked to drive his/her own wheelchair which is used in his/her everyday life. The acceleration value was measured about 20 minutes per person continuously, and the routes was selected as including some mobility barriers of wheelchairs, such as sidewalk curbs or tactile indicators for dealing with a lot of and various wheelchair driving action patterns.

In terms of classifying wheelchair driving behavior, it is important to prepare the precise supervised data, which are tuples of three-axis acceleration values and video data taken from the back of wheelchair at the experiment in our case. Thus, we use the single person's data whose acceleration values and video data were mostly correct. The data has comparatively little missing of acceleration values, and wheelchair-driving action could be judged using video data at almost all time.

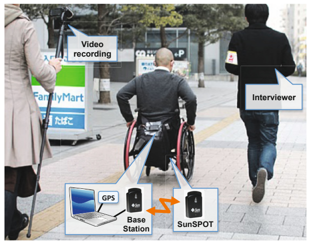


Fig. 2. System of life-logging wheelchair driving data

Figure 3 shows the histogram of sampling time of acceleration values. Horizontal axis indicates sampling time and vertical axis indicates the number of frames. As a result, the sampling time varied widely and the mean of sampling rate was about 15 Hz instead of the theoretical sampling rate of Sun Spot, 50Hz. Naturally, it is desirable that sensor data is taken as precisely as possible. However, such a precise data is not always available in actual environment. Accordingly, we investigate the available classification and accuracy of the classification from widely dispersion of sampling rate.

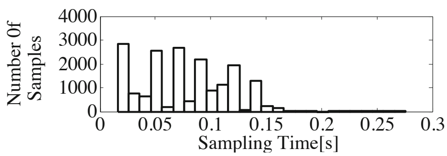


Fig. 3. Histogram of sampling time

3.2 Classification Method

Having cleared the features of using data, next I would like to explain about classification method of acceleration time-series data. SVM, a novel machine learning technique, was used to classify the time-series of acceleration values. Concretely, we divide time-series of acceleration values into some windows by the number of frames and then classify the window using SVM. Dividing time-series data using above method causes the difference of window size because of various sampling time. Although the difference of window size can decrease the classification accuracy, however, classifying the window was conducted with accepting it.

In addition, window sizes affect the classification accuracy. For instance, classification must be difficult when the continued movement, such as climbing over the sidewalk curbs, was divided into some windows Also, window sizes affect the classification finesse because the smaller window size lead to higher time resolution. Thus, it is important to optimize the window size for improvement of performances, such as classification accuracy and fineness. Result of searching the optimized window size will be shown at chapter 4.

SVM is a supervised learning method; therefore, we need information of correct class, in which what kind of driving action is taken in each window. Correct class was confirmed using video taken from the back of wheelchair at experiment. Figure 4 shows the picture captured from the video. As seen from the figure 4, it is possible to confirm the kind of ground surface which wheelchair moves on, for instance wheelchair moving on paved asphalt at (a) and moving on rough ground surface at (b). The status of road was judged like the above example.

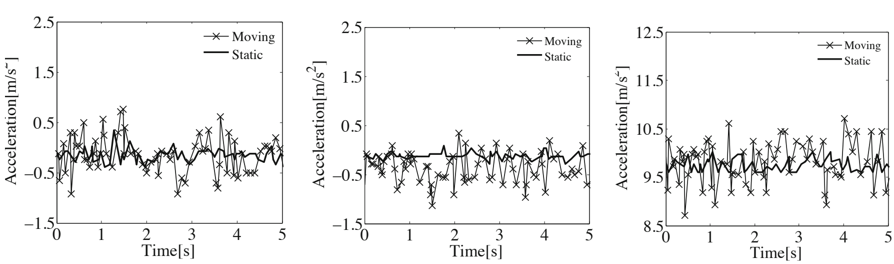
(a) (b)

Fig. 4. Video taken from the back of wheelchair at the experiment (a) moving on paved asphalt, (b) moving on rough ground surface

4 Result of Estimation and Visualization

4.1 Estimation of Human Action

Figure 5 shows the comparison between the moving action and the static action of acceleration values taken for five seconds each. Horizontal axis indicates time and vertical axis indicates acceleration value. (a), (b), and (c) represent the acceleration value of horizontal, traveling, and vertical direction of wheelchair movement. As seen from figure 5, there is big difference in two curves, that is, the curves of moving action expressed by x-mark has bigger amplitude of acceleration value than that of static action expressed by heavy line. So, it seems to be easy that we classify the driving action into moving and stopping.



(a) (b) (c)

Fig. 5. Comparison the acceleration values of moving action with static action (a) horizontal axis (b) traveling axis (c) vertical axis

Three methods were conducted in order to classify human action. The first method is simple classification that uses raw data as feature value. The second method also uses raw data as feature value but add a preprocessing to reduce the difference of window size before we divide into some windows. The preprocessing cut off frames which sampling time over the average plus 2 times standard deviation. The third method use three-axis statistics as feature value. Using statistics as feature value make the classification more tolerant for noise, though the temporal feature is rounded. As it compresses the dimension of feature value, improving the generalization ability is also expected.

Figure 6 shows F values of the above three classification methods as for each action class. Horizontal axis indicates the number of frames in a window and vertical axis indicates average of 100 F value which was calculated by 10-fold cross validation. Although F value was calculated from 5 frames to 120 frames step by 1 frame, figure 6 shows the result of 5 frames to 120 frames step by 5 frames because of the restriction of space. The missing value in figure is not a number because of few windows of static class.

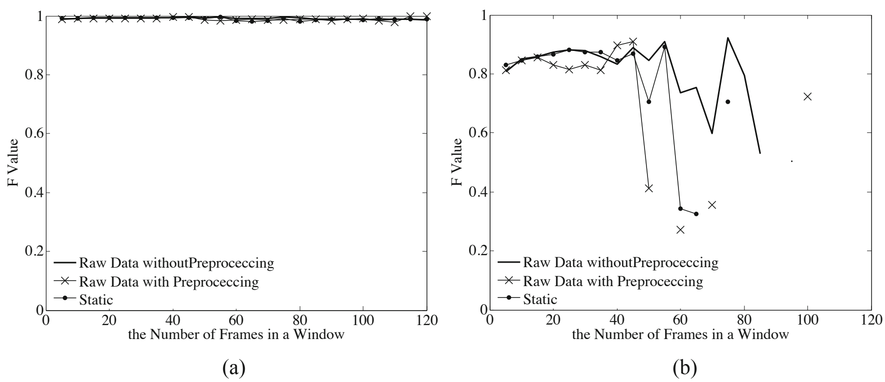


Fig. 6. F value comparison between three classification method (a) moving action class (b) static action class

As the figure 6 indicates, F value of moving action class was very high. To put it more concretely, the value was greater than 0.978 in each classification method and window size. On the other hand, F value of static action class was low than that of moving action class and tended to remarkably decrease when the number of frames is bigger than 55 frames. Comparing the result of each method, there was no big difference in both classes, however, when we focused on the area of the number of Frame which achieve high F value, classification using raw data without preprocessing (heavy line in figure 5) was better than the other methods. This result suggests that the preprocessing and using statistic value were of no effect to improve the classification accuracy. Hence, it seems reasonable to use raw data for classifying the time-series acceleration values into moving action class and static action class.

Table 1. Concrete classification accuracy at 25, 35, 45, 55 frame

the Number of Frames	Accuracy	Recall Ratio (Moving)	Recall Ratio (Static)	Precision Ratio (Moving)	Precision Ratio (Static)
25 frames	98.85%	99.30%	89.66%	99.49%	86.47%
35 frames	98.80%	98.98%	94.12%	99.76%	78.75%
45 franes	99.04%	**99.31%**	92.86%	99.70%	**85.10%**
55 frames	**99.30%**	99.27%	**100%**	**100%**	83.33%

Let us examine the classification using raw data without preprocessing in more detail. Then F value of moving class tended to be high when the number of frames was from 25 to 75, and that of static class tended to be high when the number of frames was from 25 to 55. Thus, optimized frames seem to be from 25 frames (about 1.75 sec) to 55 frames (about 3.85 sec) as for the classifying. Table 1 shows the concrete accuracy, recall ratio of each class and precision ratio of each class at 25, 35, 45, 55 frame.

4.2 Estimation of Status of the Ground Surface

Figure 7 shows ground surfaces chosen physical barrier for wheelchair mobility. These ground surface can cause falling down, paralyzing the limbs, or discomfort. The details are as follows; (a) rough road surface causing discomfort, (b) sidewalk curbs causing falling down, (c) tactile surface indicators and (d) tile paving with rough joint causing discomfort and paralyzing the limbs.

(a) (b) (c) (d)

Fig. 7. Examples of ground surface with mobility barriers (a) rough road surface, (b) sidewalk curbs, (c) tactile surface indicator, (d) tile paving with rough joint

(a) (b) (c) (d)

Fig. 8. Examples of road surface without mobility barriers (a) pavement, (b) tile paving with smooth joint, (c) paved Asphalt, (d) pedestrian crossing (paved Asphalt)

Figure 8 shows the other ground surfaces included in moving path, which were judged not having physical barrier. The details are as follows; (a) paved concrete, (b) tile paving with smooth joint (c) paved asphalt, (d) pedestrian crossing; paved asphalt. These ground surface cause only small risk for wheelchair mobility because it is comparatively flat.

We conducted three methods to classify the moving action into the state of moving on the ground surface having physical barrier (with barrier class) and not having physical barrier (without barrier class). Each method uses different feature value, raw data, statistic of each axis, and frequency component. It is expected that using frequency component help to classify more concretely.

F values of each method are shown in figure 9 as well as figure 6. Figure 9 (a) shows the result of with barrier class and Figure 9 (b) shows that of without barrier class. As a result, next two things were seen. Firstly, as the window size gets bigger, F value of with barrier class tended to increase, whereas that of without barrier class tended to decrease. It is inferred from this result that there was the domain which is difficult to divide into two classes in feature space. Secondly, method using statistics expressed by x-mark in figure 9 showed the highest performance in each class. Especially concerning without barrier class, the reduction of F value was gradually. In consequence, it is reasonable to use statistics as feature value in terms of maximize the accuracy of classification.

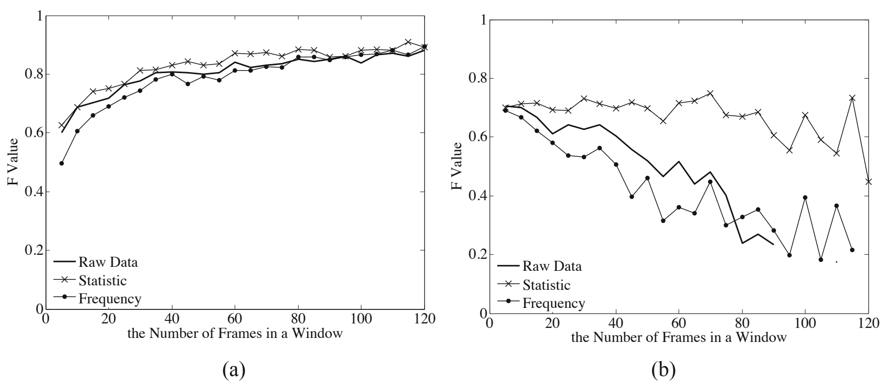


Fig. 9. F value of each classification whose feature value is raw data, statistics, and frequency component (a) moving on ground surface with mobility barrier, (b) moving on ground surfaced without mobility barrier

Figure 10 shows the accuracy curve of classification using statistic as feature value. Notation of Figure 10 similar to that of Figure 6 with the exception of that the number of frames is 5 frames to 120 frames step by 1 frame. The accuracy curve tended to increase until in front and behind of 60 frames, and to flat after 60 frames. Thus, optimized window length is bigger than 60 frames (about 4.2 sec) to classify moving class into with barrier class and without barrier class. To put it more concretely, recall ratio of with barrier class and without barrier class, precision ratio of with barrier class and without barrier class, and accuracy at the 60 frames were 89.2%, 67.9%, 85.1%, 75.5%, 82.6% respectively.

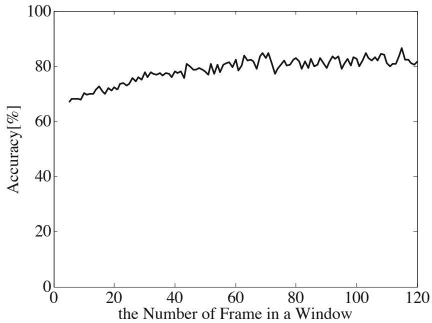


Fig. 10. The accuracy curve of classification using statistic as feature value (from 5 to 120 frames step by 1 frame)

4.3 Visualization

Figure 11 shows the result of visualizing the driving difficulty estimated through the above two classifications. High difficulty in wheelchair mobility is visualized as light shade color marker and low difficulty in wheelchair mobility is visualized as dark shade color marker. Let us look at correspondence of ground surface to visualizing result at place A to D. At the place A and C where wheelchair drove on tile paving with small joint which caused only small risk to move, visualizing result tended to be light shade color marker. At the place B having strong rough road surface and the place D being tile paving with rough joint, a lot of deep shade color marker was seen on the visualizing result. Like the above cases, visualizing result correspond to driving difficulty at least in rough point of view. Thus, to visualize driving difficulty estimated through classifications, which was shown in this paper, enables wheelchair users to judge the trends of the difficulty of terrain caused by ground surfaces.

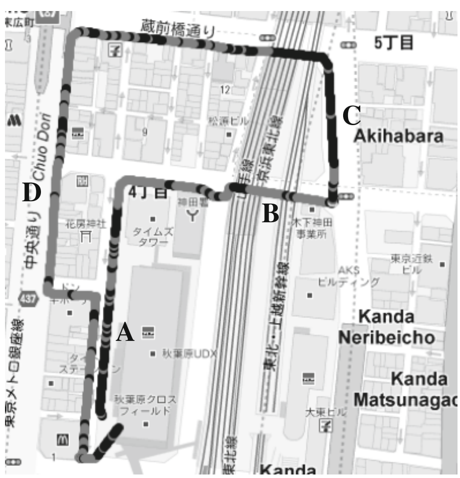


Fig. 11. Result of visualizing driving difficulty on the map

Next, we will compare our proposing approach of visualizing the difficulty with our previous approach which simply visualizes the acceleration values on trails of wheelchair. Figure 12 shows the comparison between two visualization. Each visualization use the same wheelchair driving movement data and the wheelchair drove from right to left as the heavy arrow in figure 12. The dark shade color marker means that there is no physical barrier and light shade color means that there is physical barriers in figure 12 (a), and the color is deeper as acceleration value is bigger in figure 12 (b).

Comparing two visualization at the places where wheelchair climbed over the sidewalk curbs pointed by the solid line in figure 12, there are many light shade color marker in both visualization, then we could find there was physically barrier, but, as for the places where wheelchair climbed down sidewalk curbs pointed by the dotted line, as shown in figure 12 (c), both visualization was totally different. That is, these places were estimated as physical barrier correctly by our proposing approach, and had small vibration at visualizing acceleration values, which lead the users to erroneous judge. The reason why the place caused only small vibration was the habit of the user which is decreasing the speed of wheelchair when climbed down the sidewalk curbs for avoiding the impactprobably for avoiding impact. On the other hand, such movement habit was de-noised by estimating ground surface conditions from acceleration value and that enable to judge correctly. As shown above discussion, our proposing approach was effective to digitize the potentially dangerous place and to support for wheelchair mobility.

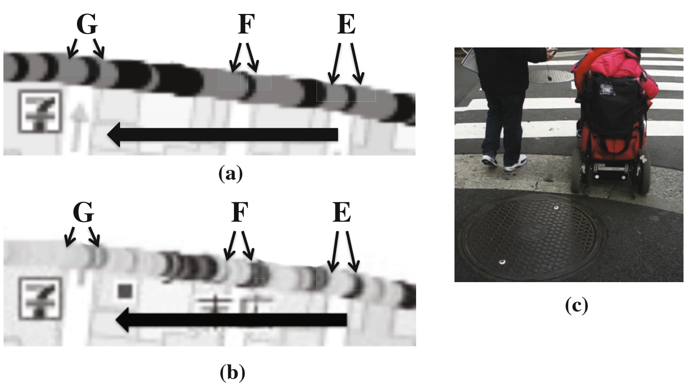


Fig. 12. The estimation result of each visualization at sidewalk curbs (a) our proposing approach, (b) visualizing VAL, (c) the sidewalk curbs

5 Conclusion

Although there is no question that physical barriers on the ground surface cause some wheelchair accidents, users can not access the information about where these accidents and incidents tend to occur because of difficulty of digitizing these information. This paper proposed to estimate the mobility barriers on the ground surface from wheelchair driving life-log measured by single cheap and mini-sized accelerometer in accordance with the classification model in Figure 1. As the results of classification, human action level classification was achieved 98.2 % accuracy rate by using raw data as feature value and setting the window size as 30 frames, and the status of the ground level classification was achieved 82.1 % accuracy rate by using statistic data as feature value and setting the window size as 60 frames, from the life-log of wheelchair driving using SVM. To visualize the estimated ground surface conditions was effective to digitize more correct information than simply mapping the VAL on Map. Open problems for developing more useful system are as follows; (1)analyzing wheelchair driving data of various properties and a large number of people, (2)reviewing another mobile and cheap sensor, such as smartphone or quasi-zenith satellites which enable to use high precision location information, to improve the accuracy of classification and to classify more complex action, (3)reviewing algorithms specialize to classify the time-series of acceleration values of wheelchair driving action into some detailed action. To clear these open problems enables us to digitize the potential dangerous place corresponding to the properties of various users and to support wheelchair mobility.

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