SpinSafe: An Unsupervised Smartphone-Based Wheelchair Path Monitoring System

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***Abstract*—**

Movement and social life of wheelchair users are constrained by their disability and suitability of paths they can move on. Modern electric wheelchairs offer them assisted drive, making their movement easier and longer. They, however, do not prevent accidents, injuries, and inconveniences caused by path roughness and ramp slopes. Providing information about suitability and accessibility of paths and buildings for wheelchair users will enable them to beforehand plan their trip to not to be caught by surprises or not to take a trip all together. The recent emergence of smartphones equipped with inertial sensors offers new opportunities for provision of information regarding quality and accessibility of paths and buildings for wheelchair users. To this end, we propose a smartphone-based participatory system incorporating a hybrid unsupervised machine learning technique based on Self Organized Maps (SOM) to identify path conditions and to create clusters of similar path types. Our solution provides useful information about the angle of the ramp and curb slopes as well as pavement quality and roughness and path types.

Keywords*—*Unsupervised machine learning, signal processing, anomaly detection, data analysis, visualization, wavelet decomposition

I. Introduction

Wheelchairs were first patented in USA in 1869, while the modern, lightweight, collapsible wheelchair we all know today, was invent in 1933. The majority of the wheelchairs do not differ much in construction. The main common features are availability of rear Φ 24” drive wheels and standard Φ 8” caster wheels, being foldable and lightweight for easy transportation, and being operated manually and/or motorized. Since their introduction they helped millions of people worldwide to have a more active social life. An estimated population of 1% in developed countries are wheelchair users[1]. These individuals use wheelchairs due to several medical and physical conditions including lower limb disabilities, Spinal Cord Injuries (SCI), head injuries, birth deformations and severe illnesses. Each condition necessitates the prescription of a special wheelchair setup. Although mobile, their locomotion is yet confined to places with appropriate paths. Authorities facilitate the mobility of the disabled users, including the wheelchair, by introducing rules and regulations considering path widths, curbs, ramp and slope angles, path pavement materials, etc [1]. While these regulations extend somehow the locomotion range, they still do not count for user conditions and situations. The scarce information regarding the pavement type, slopes and elevators, restricts prior planning for trips to be made by wheelchairs.

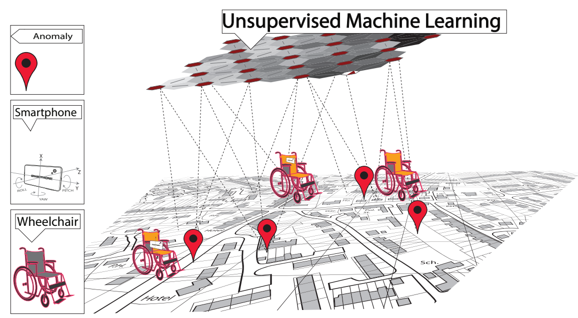

Fig. 1. The proposed smartphone-based wheelchair path monitoring system. Features are extracted from the sensor data. The algorithm clusters the features based on the pattern. The knowledge is transferred to the phone so it can independently classify the path events.

Wheelchairs are rolling vehicles prone to vibrations caused by the pavement roughness, varying in intensity and amplitude. From a mechanical point of view, they are simple rigid mechanical models, without springs, allowing the vibration to be transmitted all over the frame, including the user himself. This will expose certain categories of wheelchair users to collateral injuries. A SCI person should avoid Whole Body Vibrations (WBV) exceeding specific harmful levels that cause spasms [2]. The steep ramps and slopes can turn the wheelchair over. A trip through an improper pavement can cause the wheelchair to get stuck or even brake.

None of the existing navigational systems consider the route planning for wheelchair users. Previous research has utilized accelerometers to measure WBV and wheelchair vibrations for manual and motorized wheelchairs [3][4]. Conclusions from these studies indicate that wheelchair users are exposed to risks of secondary injuries from WBV. Cooper et al.[5] studied the effect of suspensions to reduce the shock and vibration on seat and footrest, founding that suspensions reduced the shock and vibrations, although they are not clearly superior to traditional designs. Attempts to reduce the WBV without compromising wheelchair features introduced new type of wheel constructions. Vorrnik et al. [6] compared these wheels in terms of vibration and spasticity for people suffering from SCI. They concluded that the new wheel type did not absorb or reduce the vibrations caused by path roughness. These studies indicate that accelerometers are capable of measuring the concerned vibrations induced by path roughness and the vibration level does not differ substantially

[1] http://www.newdisability.com/wheelchairstatistics.htm

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among wheelchair models. The aforementioned works used different methods for data analysis. Frequency analysis was used by [5][4], Root Mean Square (RMS) of the vertical acceleration by [3][6], and variance analysis(ANOVA) by [6]. Although, wheelchairs are not equipped with accelerometers, their users use smart-phones equipped with GPS and inertial sensors. Accelerometers and gyroscopes are able to sense the vibrations and angular changes and smart-phones can handle, process, and share that information. This will allow wheelchair users to use and update that information in real time. They can measure the path roughness, ramp or curb angle, bumps, the presence of an elevator. They can safely plan their trip according to their needs, avoiding paths and directions not suitable for their specific condition. Based on this information we propose a smartphone-based system capable of sensing path roughness and reporting critical segments of wheelchair paths. Our system supplies the wheelchair users with valuable information by differentiating through different types of pavements, showing the level of vibration for each segment, and calculating the angle of ramps and slopes through the path. The system conducts signal analysis using Stationary Wavelet Transformation (SWT) (similar to RoADS[7]) for both accelerometer and gyroscope signals. The signal analysis is performed on the premise that different pavement anomalies generate different vibrations within certain frequency bins. The width of those frequency bins depends on some physical factors such diameter of the wheel, speed of the vehicle, damping characteristics of the physical system. Our field-test results demonstrate the capability and the precision of the proposed system. Fig. 1 shows a mock-up picture of how our solution resolves the problem of wheelchair path recognition by learning from the data.

II. Related Work

OurWay [8] is a collaborative route planner in which users individually rate segments of paths to provide information tailored to wheelchair user needs and preferences. It is a mobile phone based application but does not use inertial sensors. The path segments are subjectively and manually rated by the users. Authors of [8] conclude that the users were not much interested to give feedback about the route and they only wanted the best route. This adds a strong motivation for our solution as the user does not need to give feedback. In comparison, our solution does not suggest any route, but rather gives the user the choice to select the best route based on his/her health conditions.

The most similar conceptual work to ours is WeGoTo [9]. The work focuses on obstacle denunciation on a wheelchair path, involving the use of smartphone inertial sensors. It presents a flowchart diagram describing a decision making algorithm. The algorithm classifies different states (i.e., fall, propelling, turning) with subjective results (i.e., easy, medium and hard) for the wheelchair based on orientation and accelerometer data. However, no results and evaluations were presented. Although the paper illustrates a generic chart for sensor fusion, there is no indication whether the authors implemented another Kalman filter algorithm or used Android API to obtain the orientation. Explanation is missing regarding the smartphone position relative to the vehicle frame and how, if, the reorientation is performed. According to the safety regulations regarding the sidewalk crossfall of no more than 2°, the paper fails to discuss the accuracy of the angle estimation. The same can be said for the ramp and slope angle calculations. The authors choice to analyze the low pass filtered accelerometer data, when they initially claimed the use of a Kalman filter remains unclear. The paper mentions frequency analysis and signal energy but does not elaborate further at which frequency bins that energy was concentrated.

III. Methodology

This section describes our methodology and the techniques used. We first start by performing a thorough analysis of construction, types and the structure of wheelchairs as well as the dynamics and features of paths they ride on. We then continue by analyzing what can be measured, how these measurements can be transformed into more meaningful information, and how data should be processed and handled.

The front wheel called caster usually has a diameter of 8 inch and it is quite narrow to facilitate the propulsion of the wheelchair. The drawback of a small diameter caster is that it is prone to continuous vibration. Driving the wheelchair on asphalt pavement will generate higher frequency low amplitude vibrations. Whenever the wheelchair drives on bricked pavement, low frequency vibrations will be generated corresponding to the frequency of the gaps between bricks on the floor. The speed of the wheelchair, as in all rolling vehicles, modulates the amplitude and frequency of those vibrations. At higher speeds the amplitude of the vibration for the same anomaly will be higher. Another factor to consider is the wheelchair construction, in a way that the two lateral sides are quite independent of each other. They act as suspension, and the siting part with the rear wheels act as a dumper. Fig. 2 illustrates a wheelchair, its accelerometer and gyroscope signals for different type of pavements for a 5 second ride. As it can be seen from Fig. 2a, the max amplitude of vertical acceleration on a flat indoor pavement is $1.4m/s^2$ and the gyro angular velocity is $\omega\ 0.2rad/s^2$. With the transition to a rougher brick pavement as shown in Fig. 2b, the wheelchairs becomes more shaky and the amplitude of the vertical acceleration raises to $10.5m/s^2$ as well as $\omega = 0.5rad/s^2$. In the first 2 seconds, the speed is low and the spikes caused by the inter-brick gaps can clearly be observed. On an unpaved surface as illustrated in Fig. 2c, the amplitude of vertical and lateral acceleration spike to $10.5m/s^2$ and $\omega = 1rad/s^2$. When following a ramp as shown in Fig. 2d, the roll axis of the gyroscope measures the angular change during the transition point of the ramp slope. Following this simple reasoning we can assume that by analyzing this axis of accelerometer and gyroscope we will be able to detect the pavement types, elevation as well as bumps and obstacles.

However, analyzing the signal in time domain is not enough as the signal is composed of different vibration elements that are modulated together. Also the pavements are not always as simple as shown in Fig. 2. Most of the time, the paths are not flat, the surface gets more rough as it ages, the tree roots, manholes, sunken pavements make the surface uneven resulting in bumpy roads

A. Signal analysis and transformation

Frequency domain (FD) transformation allows us to analyze the frequency components of the signal. However FD is more suited for narrow band stationary signals.

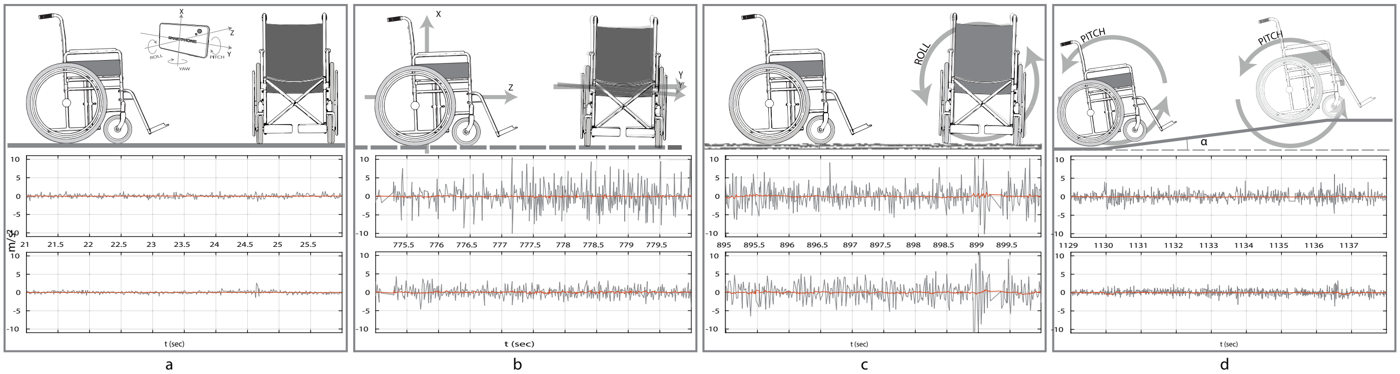

Fig. 2. Wheelchair measurements over different type of surfaces. Wheelchair a) riding a smooth indoor surface, b) riding tiled with big gaps pavement, c) riding an unpaved but well pressed gravel pavemetn, d) entering a ramp

The RoADS [7] uses Stationary Wavelet Decomposition (SWD) to decompose the sensor signals into 4 levels using Symlet sym4 wavelets. Wavelet decomposition provides an alternative way of signal processing, it has a good time and frequency resolution for both low and high frequencies, and is better suited for analysis of sudden and transient signal changes and analyzing irregular data patterns such as impulses generated at different time instances.

Considering the speed of the wheelchair to be at $6km/h$ or $1.7m/s$ and the sampling rate of the smartphone sensors to be at 60 samples/s, a 128sample window corresponds to a distance up to 3.2 m, suitable to capture all the low frequency bumps on the path, the full anomaly can reside inside one window.

B. Learning and path classification

One of the main concerns of any classification is setting the ground truth and comparing the results with that. The algorithm should detect different types of anomalies. This is a rather challenging task, especially when aiming to implement it on smartphone platforms with limited energy supply and processing power. There are two approaches to the problem of anomaly detection, i.e., *i)* supervised learning and *ii)* unsupervised learning. The first approach relies on the premises of knowing beforehand the classes to be classified. Using a handful of data representing those classes, a classifying algorithm can be taught to distinguish between them. Then performance of the algorithm is tested using unknown data sets by manually checking the results. The alternative approach is the unsupervised learning method. The method tries to create clusters of data with similar attributes. Choosing the right method depends on the task and the complexity of the data to be classified.

Taking all these into consideration, we decided to use unsupervised machine learning techniques, namely the Self-Organizing Map (SOM) Neural Network [10][11]. The SOM algorithm is based on unsupervised, competitive learning. It is appropriate for clustering problems, i.e. grouping different elements according to the similarity in pattern and feature set. SOM is inspired by the way the brain stores and organizes the information, by storing the correlated information in close by area. SOM creates a bi-dimensional map of neurons in which the input features are grouped through a neighborhood function that calculates the degree of similarity between them. Features representing similar information will be closer on the neuron map. Fig. 3 shows a typical visualisation of a SOM neuron network lattice. The features are recursively shown to each of the neurons. The neighbourhood is characterized by the distance between neurons. Dark colors represent longer distances, the distance is the difference between the pattern features. We can summarize the behavior of a SOM network in the following steps: Consider a feature set D, the feature n belonging to D^i, where i is the index of the feature vector. The algorithm calculates the Euclidean distance of $D^i(n)$ and the weight W of the neurons v. The neuron that produces the shortest distance is called Best Matching Unit(BMU) and is indexed u. The BMU has neighbour neurons. Neighbourhood radius is restrained with a neighbourhood function $\Theta\left(u,v,s\right)$. Both BMU and neighbours are updated giving them a weight closer to $D^i(n)$ as following:

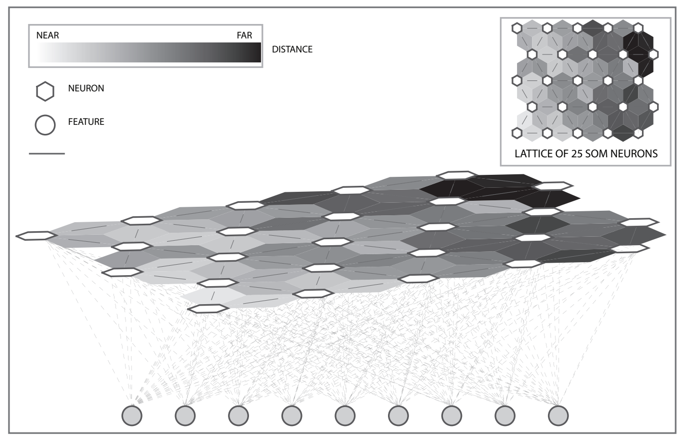

Fig. 3. Typical visualisation of Self Organizing Maps

$$W_v\left(s+1\right) = W_v\left(s\right) + \Theta\left(u,v,s\right)\alpha\left(s\right)\left(D^i\left(n\right) - W_v\left(s\right)\right) \tag{1}$$

, where s is the current epoque to be no more than a limit denoted by λ.

This way a high dimensional space can be mapped into a plane. SOM property of *topology preserving* means that feature vectors preserve their relative distance also into the plane, ie. feature vectors that are close to each other in the input space are mapped to nearby neurons in the SOM. This property allows SOM to serve as a clustering tool for high-dimensional data. The SOM network has also a generalization capability, recognizing features never seen before, by assimilating the feature within the neuron it is mapped to.

Based on aforementioned analysis, the extracted features from accelorometer sensor axis will create a high dimensional feature space with enough information to contribute on clustering together similar patterns. The SOM is trained with the collected data and the formed cluster are manually compared with the known path segments transforming the clusters into labelled classes.

C. Ramp and curb angle calculation

Wheelchairs are quite narrow vehicles and their center of gravity is also quite high, making them subject of accidents when passing through steep ramps and curbs. Although rules and regulations sanction the safety parameters for the slope, they cannot satisfy all the cases. For the safety of the wheelchair user, a slope should be a least with a ratio 1:12 corresponds to an angle of $\approx 5°$. In [12], a method to calculate the angle of the turn using gyroscope Yaw axis was introduced. We use the same method to calculate the slope angle of the gyroscope Pitch axis and also the angle of the curb using the information from Roll rotation. When the wheelchair enters a ramp, a rotation on the lateral axis, i.e., Pitch axis, is registered. The gyro signal changes at the slope and at that precise moment the algorithm starts the integration of the angular velocity, using the smoothed signal from mean of the windows. If the angle at the peak of the signal is less than $1.5°$, the integration is dropped as the slope is not too steep. This way all slopes more than $3°$ can be precisely detected.

IV. Evaluation

We evaluate performance of our wheelchair path monitoring algorithm empirically through experiments. The experiments were conducted in two different geographical places. Table I gives an overview of the experimental setup. Two motorized wheelchairs operated by their experienced users collected data in motorized and manual mode in different urban and indoor paths in Singapore. Two manually operated wheelchairs were used to collect data at the campus of the University of Twente in Enschede the Netherlands. We perform the experiments at least twice for each path.

A. Experimental setup

The selected paths were chosen in such a way to include all types of terrains possibly a wheelchair user will usually pass through. This includes asphalt, bricked sidewalks, wooden and metallic bridges, ramps and slopes, elevators, manholes, and curbs. The trips in Singapore experiments contain video footage recorded by the smartphone's back camera and two of the trips were labelled. The wheelchairs were fitted with an accelerometer (fixed at the center of the frame) and two smartphones (one fixed with a holder to one side of the wheelchair armrest and the other one on the chest of the user). Experiments in Singapore were performed in indoor shopping malls and the paths surrounding them. Experiments with manual wheelchairs at the university campus were performed using two smartphones, one fixed on the side of the wheelchair armrest and the other laying on the seat between the legs of the user. Photos of the path ahead were captured every 10 seconds. These experiments were conducted in outdoor environments, covering different scenarios ranging from asphalt, brick paths, gravel paths, bridges, parks etc.

TABLE I. Experimental setup

Inventory	Singapore		Netherlands	
Mounted sensor				
	MbientLab Metawear		None	
Acc	50 Hz			
Position	Center frame			
Smartphone				
	Samsung S4	Samsunge Note 3	Samsung S4 mini	Motorola Moto G
Acc	92Hz	50Hz	75Hz	97Hz
Gyr	92Hz	50Hz	135Hz	185Hz
Position	armrest	carried	armrest/carried	armrest
Wheelchairs				
Model	Yamaha JWX-1	Merits P201	Unknown	Unknown
Propulsion	Electric/Manual	Electric/Manual	Manual	Manual
Main Wheel	24" pneumatic	14" foamfilled	24" pneumatic	24" pneumatic
Caster	8"pneumatic	8" foamfilled	8" pneumatic	8" pneumatic
Speed	6 km/h	6.4 km/h	6.5 km/h	6.5 km/h
Weight	14.7 kg	78 kg	$<$10 kg	$<$10 kg
Nr. Trips	3	2	13	7
Photo/Video	Video	Video	Photo 1p10s	Photo 1p10s
Distance	6.3 km		20 km	

B. Data preparation

The linear acceleration, i.e., the acceleration signal without the gravity component, and the gyroscope signal for their respective three axis were collected with the highest possible sampling rate allowed by the Android OS. The GPS signal were sampled with 1 sample per second. The data was windowed in segments of 2 seconds with 2/3 overlap. The signal was decomposed through STW at four levels of decomposition with a sym5 wavlet. The following features were extracted for all levels of approximations and details:

- mean
- mean absolute deviation
- standard deviation
- variance
- RMS
- energy

The overall feature set per window consists of 288 features. Because the SOM calculates the Euclidean distance between the features, the feature vectors were normalized to have an Euclidean distance of 1:

$$x_i^{'} = \frac{x_i}{\sqrt{\sum_i^n x_i^2}} \tag{2}$$

C. SOM evaluation

The appropriate dimensions for the neuron lattice is determined by training the SOM with different dimension parameters and feature sets. The aim is to find a specific number of neurons that sufficiently detects the path segments. The performance of each SOM dimension is tested on a set of labelled data. Fig. 8 shows the results of clustering for the four states shown in Fig. 2 using a 16 (4x4) and a 25 (5x5) node SOM. By visual inspection of clustered neurons in the lattice of Fig.5, the tendency to create 2 distinctive clusters that do not belong to different anomalies but rather to the data collected by the carried and mounted smartphones becomes

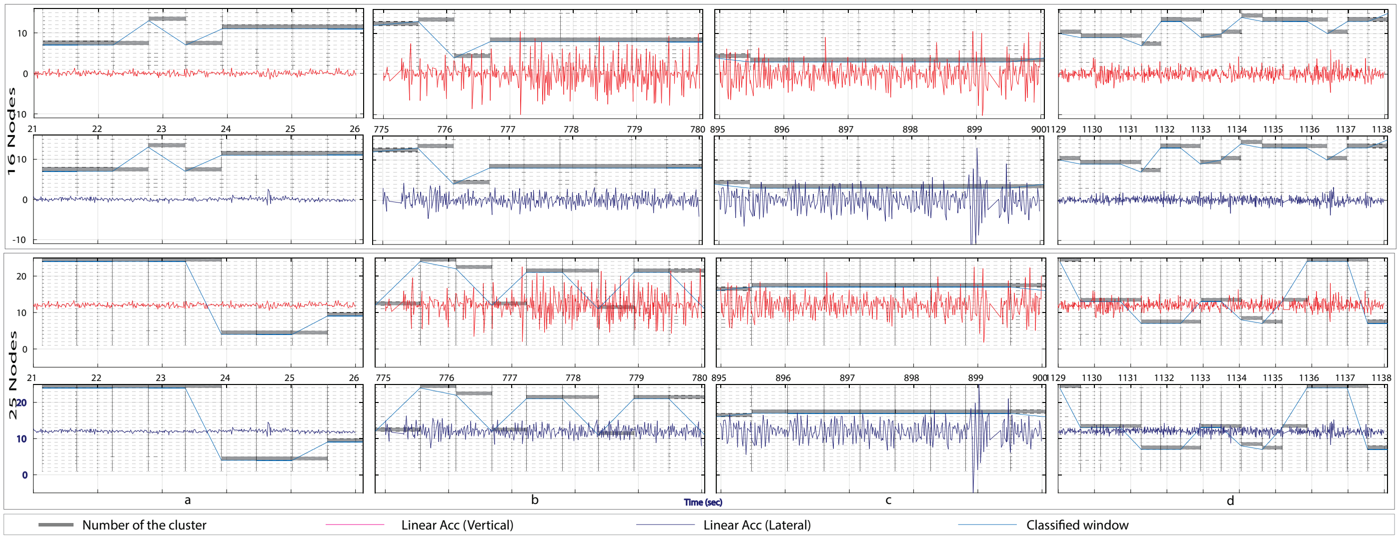

Fig. 4. The signal from Fig:2 clustered with SOM 16 nodes above and 25 Nodes below. a) riding a smooth indoor surface, b) riding tiled with big gaps pavement, c) riding an unpaved but well pressed gravel pavement, d) entering a ramp

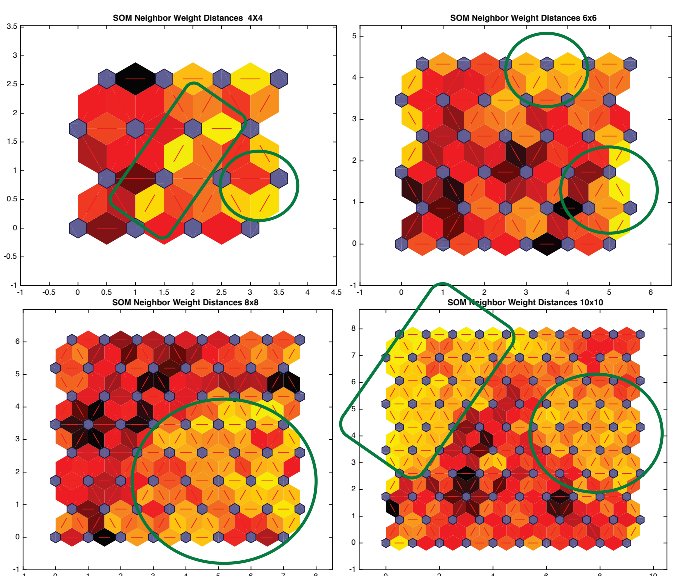

Fig. 5. SOM neighbor distances for 4 different neuron lattices. The light coloured distances correspond to the created cluster of neurons in a neighbourhood.

clear. The pattern of cluster formation is consistent with the one of 4x4 lattice as well.

We evaluate the performance by first of all identifying the path segments and annotating their start/stop coordinates making them partially labelled segments (the type of path is known but not any particular bump). KML files are generated for each trip and each class of the trip with segment number. The results for each segments show how many data windows are mapped to the neurons representing that path type for both mounted and carried smartphones. The KML files are mapped on the Google Earth and the correctly clustered segments are counted. This procedure is repeated for different lattice dimensions. A higher dimension of neurons will create more defined clusters. Even though during the experiments we tested

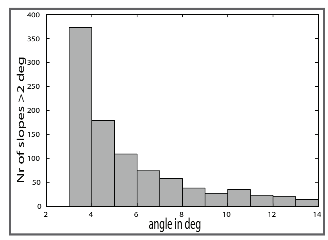

Fig. 6. Slope angle distribution

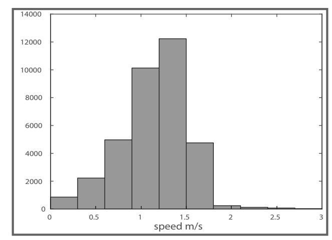

Fig. 7. Speed histogram

different combination of latices up to latices of 10x10 neurons, for evaluation simplicity we decided to use a 25 node SOM.

Fig. 9 shows results of clustering procedure for the data collected in Singapore. It can be seen that data is clustered into brick paths, small bricks and asphalt, and mild bump anomalies. The video footage shows that experienced wheelchair users are cautious, always following safe paths, although they were instructed to collect more rough path segments. Another important reason is that experiments took part in indoor or semi indoor facilities. Nevertheless the user were perfectly satisfied with the results. Fig. 8 shows results of clustering procedure for the data collected in the Netherlands. It can be seen that results are more diverse as more possible paths outdoors were covered in the experiments.

The severe bumps, bridges and other severe anomalies are detected by both mobile phones, i.e., carried by the user and mounted on the seat of the wheelchair. One may note that the signal from the carried phones are clustered by other neurons, not related to the neurons responsible to cluster data from mounted phones. We observe that the 3x3 SOM lattice was not able to classify correctly all the path events. The results are inconsistent and not correlated.

D. Slope angle calculation

The slop angle is calculated with the algorithm proposed in [12], replacing the Yaw with the Pitch axis of the gyroscope.

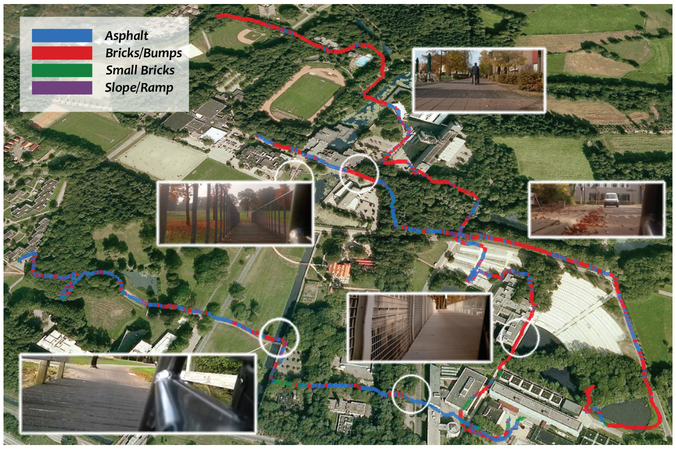

Fig. 8. The results in UT Campus

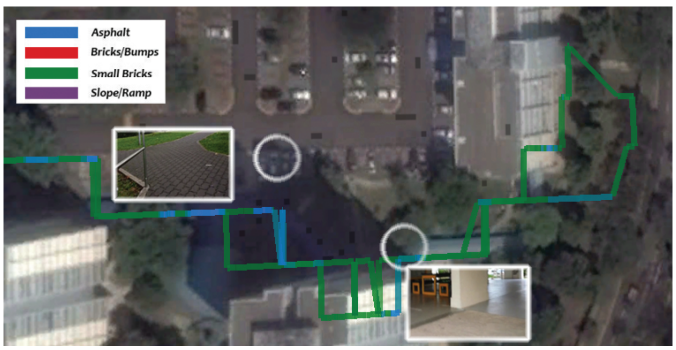

Fig. 9. Singapore neighbourhood

Fig. 7 shows calculated angle distribution for detected slopes more than 2° over all experiments. The wide slope angles above 5° are not physical slopes but user interaction with the wheelchair. The wheelchair can incline backward when the big wheels are rapidly turned backwards. This is usually done when the user wants to pass an obstacle in front of him. The calculated angle was consistent for both mounted and carried smartphones.

V. Conclusion

In this work we presented a system that helps the marginal category of wheelchair users to conduct a more active and safe lifestyle, by allowing them to monitor in real time the paths they drive on. The proposed system is based on the ability of the Self Organized Maps (SOM) to divide the smartphone collected sensor data features into clusters corresponding to different path pavements and path anomalies. Performance evaluations are done using different scenarios with smartphones mounted on wheelchairs and carried by the users, on different path types, on smooth indoor floors and rough outdoor pavements, and with different wheelchair types. Our experimental results show that our system is able to correctly detect dangerous situations related to steep ramps and curbs by calculating the Pitch and Roll angle of the wheelchair in these situations. SOM unsupervised learning algorithm and the SWT wavelet decomposition proved to be great tools for clustering and classification of the non-stationary signals, like the ones collected by mobile phones. Our future work includes design of a continuous learning algorithm in which smartphones collaboratively will increase their knowledge base.

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