Mobile Application for Naturalistic Walking/Cycling Data Collection

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IN-DEPTH UNDERSTANDING OF ACCIDENT CAUSATION FOR VULNERABLE ROAD USERS

Project No. 635895 — InDeV

InDeV: In-Depth understanding of accident causation for Vulnerable road users

HORIZON 2020 - the Framework Programme for Research and Innovation

Deliverable 4.5

Mobile Application for Naturalistic Walking/Cycling Data Collection

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Document information

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3	17-10-27	Document compiled by Thomas and sent into internal review (Nicolas Saunier)
4	17-10-31	Document updated based on comments from internal review

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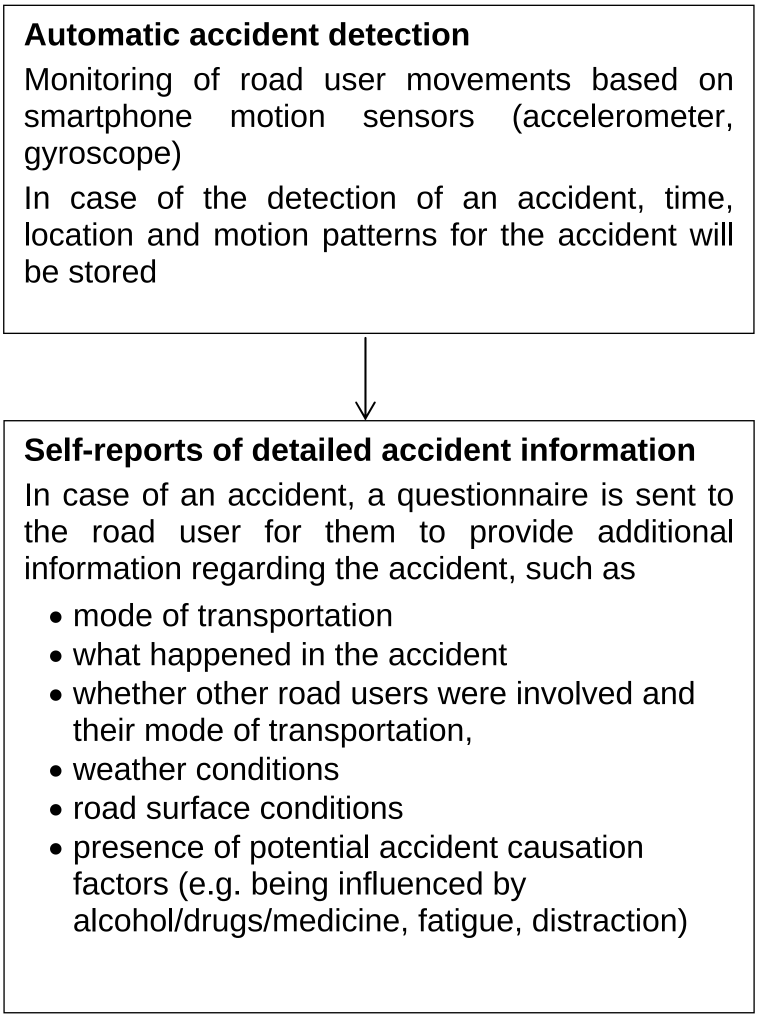
Executive Summary

The use of technology to aid the data collection process is sound. The alternative requires too much manual labour. This report describes two smartphone apps that was developed towards the aim of harvesting insights of VRU and accidents.

These two apps require a backend database with software tools for generating and managing questionnaires etc. Such a system was developed using a MySQL database where a user-friendly platform has been developed in CakePHP. The backend system has been successfully developed and been used to handle more than 11,000 participants.

The original idea was to monitor VRU via apps to detect when they may have been involved in an accident as pedestrian or cyclist based on the motion patterns from the smartphone's motion sensors (accelerometer, gyroscope) and collect as much information as possible regarding the accident automatically (e.g. time and location of the accident). If an accident was detected, the road user should receive a questionnaire to provide detailed information of the accident (e.g. road surface conditions, lighting conditions, other road users involved). The concept is illustrated below.



Automatic accident detection

Monitoring of road user movements based on smartphone motion sensors (accelerometer, gyroscope)

In case of the detection of an accident, time, location and motion patterns for the accident will be stored

Self-reports of detailed accident information

In case of an accident, a questionnaire is sent to the road user for them to provide additional information regarding the accident, such as

- mode of transportation
- what happened in the accident
- whether other road users were involved and their mode of transportation,
- weather conditions
- road surface conditions
- presence of potential accident causation factors (e.g. being influenced by alcohol/drugs/medicine, fatigue, distraction)

A smartphone app was developed to automatically detect accidents by analysing the motion data of the phone. The underlying idea is that accidents result in abnormal movement compared to everyday activities and hence by analysing movements, accidents can be detected automatically. Realistic training data was collected using a stuntman and a dummy doll. Both a simple rule-based approach as well as a more advanced machine learning approach were developed and tested. It seems that accidents can be predicted by rule-based or learned models, but fails to generalize across devices since different motion sensors on different smartphones react differently and require tedious individual calibration. It was therefore decided not to ask participants to download and implement the developed apps. Instead a smartphone app was developed for self-reporting. This app was used by more than 400 participants resulting in a large amount of data that are currently being analysed. It is expected that this data will result in valuable insights into VRU and accidents.

1. Introduction

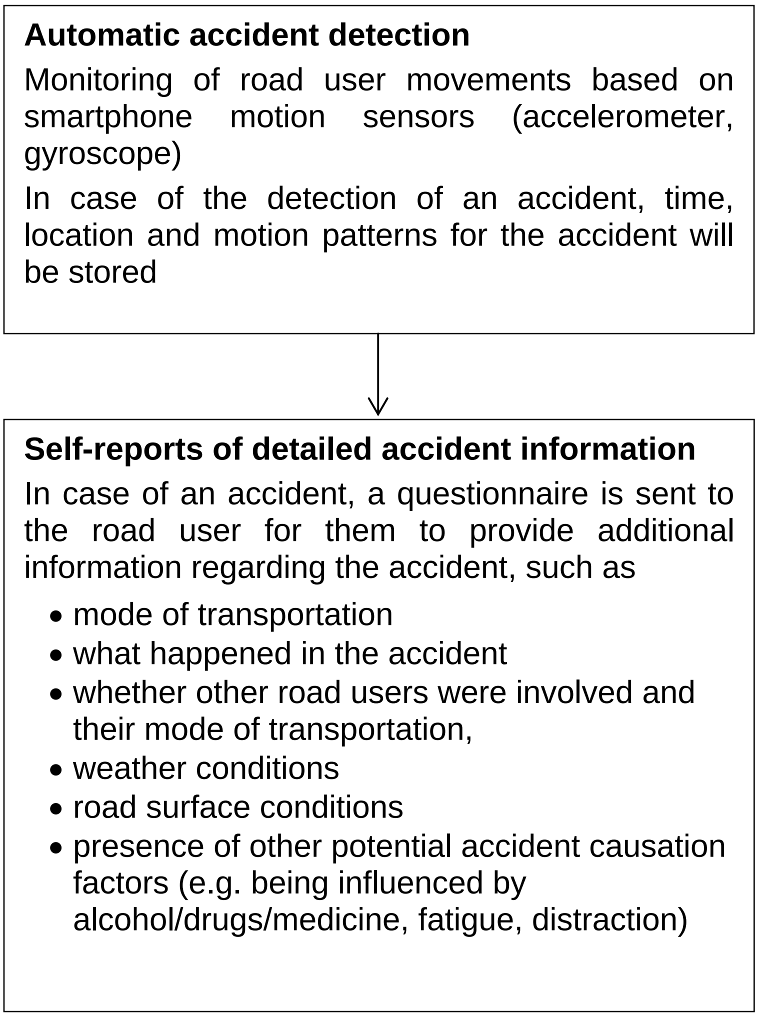
Naturalistic studies are used to conduct behavioural studies of road users. In a naturalistic study the road user is observed over a long time while travelling in their own means of transport during their daily trips, as they would normally do, with no instructions and no intervention as regards to how, where and when to travel. Information regarding a large range of characteristics (e.g. speed, performed manoeuvres, video footage of surroundings and of the road user) can be collected continuously via equipment such as accelerometers, gyroscopes, GPS receivers, video cameras and switches connected to the vehicle.

Often, naturalistic studies involve a large number of road users who collect data over a long period of time, e.g. months or years. Thus, near-accidents or accidents will eventually be captured, providing important information about the moment before and during the incident, which can contribute to a better understanding of how and why accidents occur, and ultimately help to reduce the number of accidents.

Due to a large range of data sources and long study duration, the amount of data from a naturalistic study is large. Consequently, it can be very time consuming to analyse the data. It is therefore of great importance to develop automated methods that can assist towards this goal.

2. Approach

In this study, focus has been on developing a system in two parts: an app for automatic detection of accidents of pedestrians and cyclists, and a questionnaire for self-reporting of detailed accident information. The basic idea is to monitor the road users to detect when they may have been involved in an accident as pedestrian or cyclist based on the motion patterns from the smartphone's motion sensors (accelerometer, gyroscope) and collect as much information as possible regarding the accident automatically (e.g. time and location of the accident). If an accident was detected, the road user should receive a questionnaire to provide detailed information of the accident (e.g. road surface conditions, lighting conditions, other road users involved).



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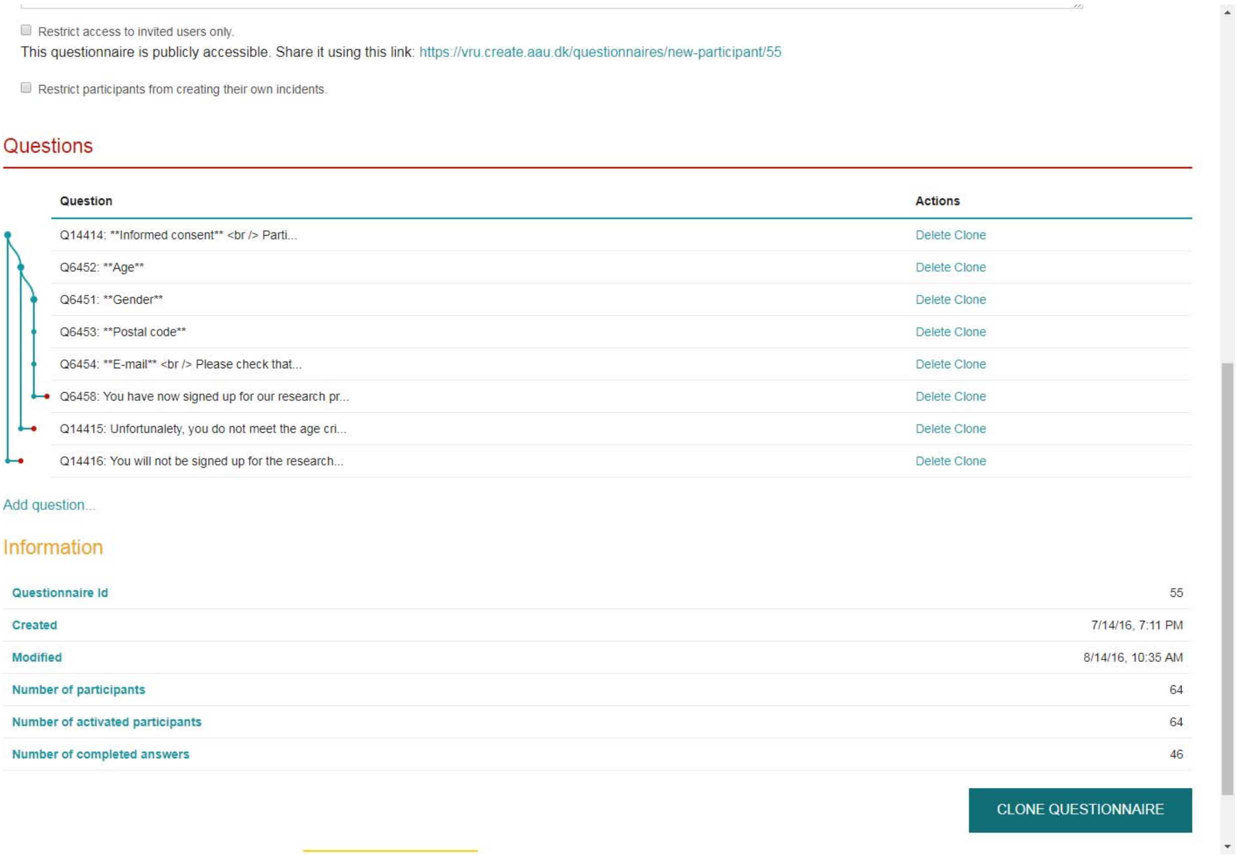
- whether other road users were involved and their mode of transportation,
- weather conditions
- road surface conditions
- presence of other potential accident causation factors (e.g. being influenced by alcohol/drugs/medicine, fatigue, distraction)

In the study, the automatic accident detection and the system for self-reporting of accidents were developed and tested separately.

3. Self-reports (Questionnaires)

For caretaking the self-reporting questionnaires, a strong backend infrastructure is created to facilitate the potential high number of participants. The backend for the self-reporting questionnaires mainly consists of a MySQL database where a user-friendly platform has been developed in CakePHP. The platform allows administrators to securely login and get an overview of all the active questionnaires and more importantly create new questionnaires and manage existing ones (Figure 1). The database has been developed so that the questionnaires can take a very complex and tree-like structure, e.g. different routes in the series of questions depending on your answers.



□ Restrict access to invited users only.

This questionnaire is publicly accessible. Share it using this link: https://vru.create.aau.dk/questionnaires/new-participant/55

□ Restrict participants from creating their own incidents.

Questions

Question	Actions
Q14414: **Informed consent** <br /> Parti...	Delete Clone
Q6452: **Age**	Delete Clone
Q6451: **Gender**	Delete Clone
Q6453: **Postal code**	Delete Clone
Q6454: **E-mail** <br /> Please check that...	Delete Clone
Q6458: You have now signed up for our research pr...	Delete Clone
Q14415: Unfortunalety, you do not meet the age cri...	Delete Clone
Q14416: You will not be signed up for the research...	Delete Clone

Add question...

Information

Questionnaire Id	55
Created	7/14/16, 7:11 PM
Modified	8/14/16, 10:35 AM
Number of participants	64
Number of activated participants	64
Number of completed answers	46

Figure 1: Platform for creating and managing questionnaires and responses from the questionnaire.

The administrator can also examine a specific questionnaire and send out reminder emails, e.g. to all the participants or to some specified participants that are missing some answers.

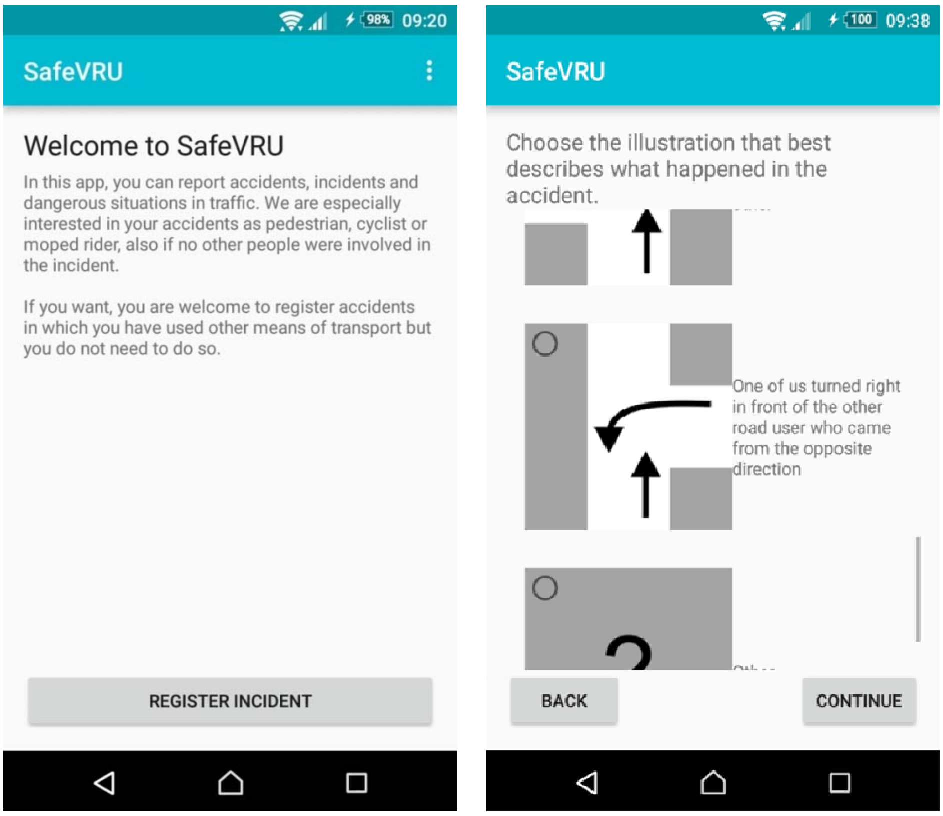
In addition to this web-based part, the backend must also be able to handle the communication with the participants. To do this, database handlers are implemented with the purpose of securely fetching questions from a given questionnaire for a participant and storing the corresponding answer safely in the database.

For the self-reporting of accidents, an Android app, *SafeVRU*, was developed (Figure 2).

Accidents could be registered in two ways:

1) the participants press a button in the app after they have had an accident or near-accident,
2) once every month, the participants receive a push notification[1] prompting them to answer a questionnaire asking if they have experienced any accidents during the past month.

In both cases, a questionnaire with questions about the nature of their accident is used in case that they confirm that they have had an accident in the first question of the questionnaire. These questions concern the time of the accident, their mode of transportation, what happened in the accident, whether other road users were involved and their mode of transportation, weather conditions, road surface conditions as well as a question regarding accident causation factors (e.g. being influenced by alcohol/drugs/medicine, fatigue, distraction).



Welcome to SafeVRU

In this app, you can report accidents, incidents and dangerous situations in traffic. We are especially interested in your accidents as pedestrian, cyclist or moped rider, also if no other people were involved in the incident.

If you want, you are welcome to register accidents in which you have used other means of transport but you do not need to do so.

Choose the illustration that best describes what happened in the accident.

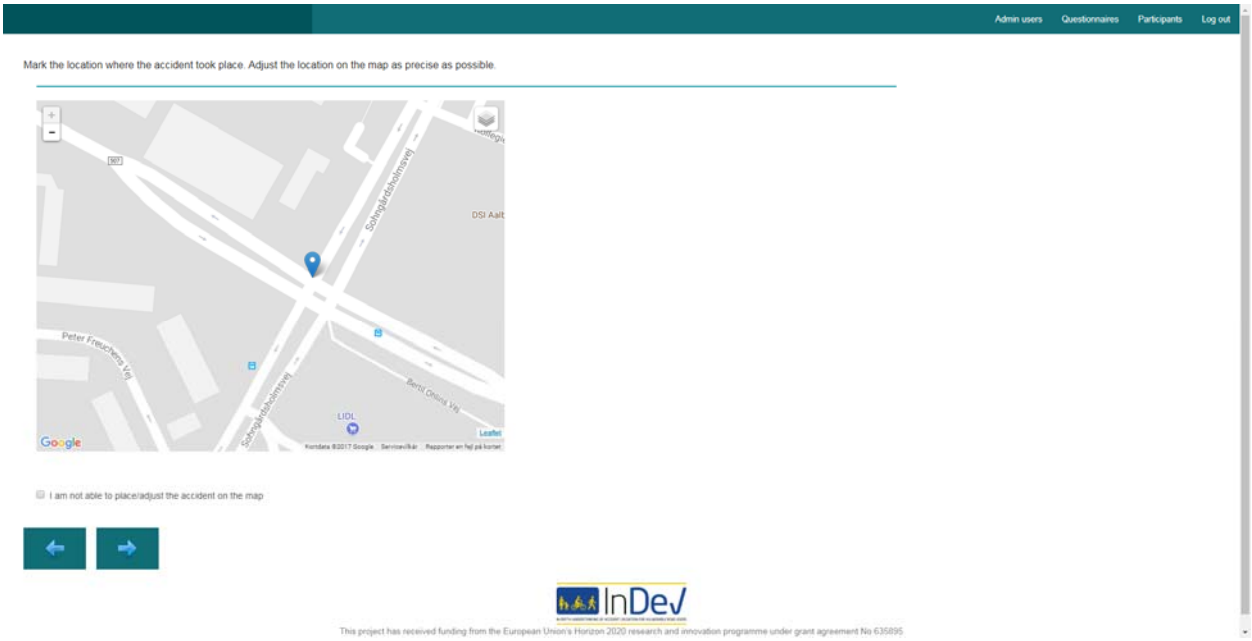
○ One of us turned right in front of the other road user who came from the opposite direction

○

Figure 2: SafeVRU app for self-reporting of accidents and near-accidents. The user could press a button; ”register incidents”, to report a (near-)accident (left) and would then be directed to the questionnaire to provide detailed information, e.g. regarding what happened in the accident (right).

[1] Push notifications did not work on all smartphones, e.g. because the participant had chosen not to receive push notifications.

A web-based questionnaire was made for those who did not own an Android smartphone or preferred to fill out questionnaires from their computer (Figure 3).



Mark the location where the accident took place. Adjust the location on the map as precise as possible.

□ I am not able to place/adjust the accident on the map

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 635895

Figure 3: Web questionnaire

4. Automatic detection of accidents

Two different approaches have been followed and these are described below. But first it is explained how training data was obtained by simulating accidents.

4.1. Simulated accidents

Simulated cycling and walking accidents were performed by a stuntman and with a crash test dummy (Figure 4) to use for the development of algorithms for automatic detection of accidents of pedestrians and cyclists.

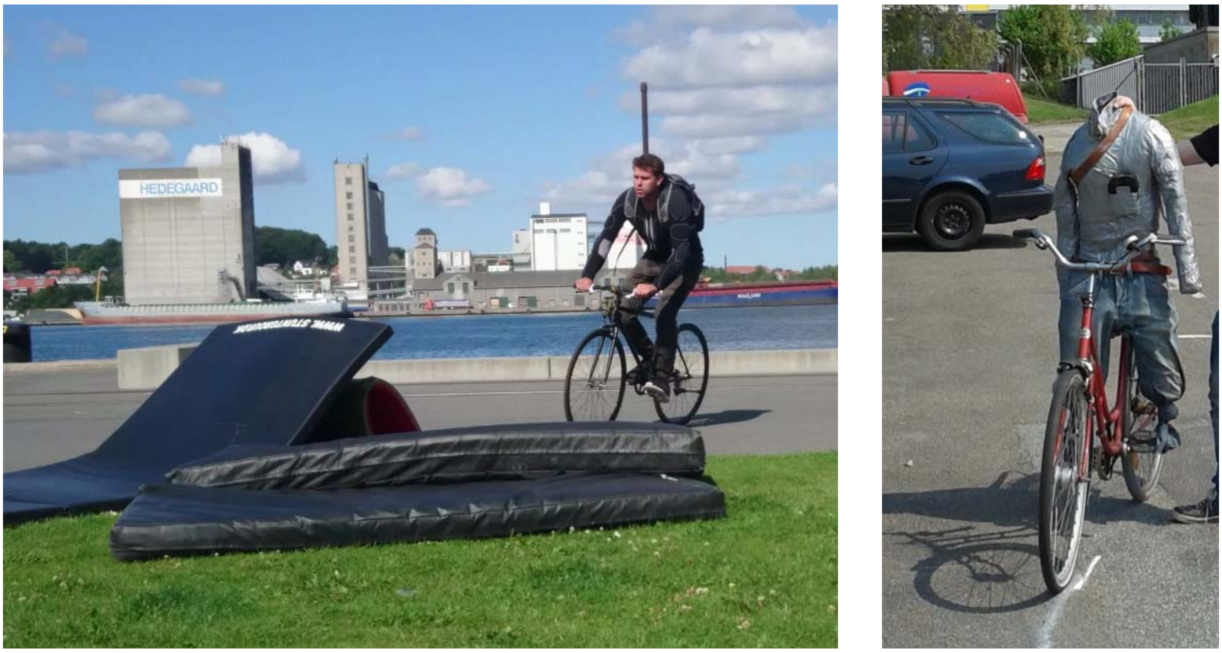


Figure 4: Stuntman (left) and crash test dummy (right)

The data collected consisted of simulations of common accident types for cyclists and pedestrians:

1) The bicycle suddenly stops, and the cyclist falls forward over the handlebars
2) The cyclist hits an obstacle (e.g. a curb) and falls to the side
3) The pedestrian trips over an obstacle (e.g. a curb) and falls forward
4) The pedestrian trips over an obstacle (e.g. a curb) and falls to the side
5) The pedestrian slips on ice and falls backward

The stuntman performed simulations of type 1-4 with the smartphone placed in three different locations (trouser pocket, chest pocket and backpack). All scenarios were performed three times except for forward cycling falls with the sensor in a backpack, which was only simulated twice as the bicycle broke down. In total, 35 accidents were simulated by the stuntman. Mattresses were used in all cycling simulations to protect the stuntman. The pedestrian falls were performed on a hard mattress or directly on the lawn.

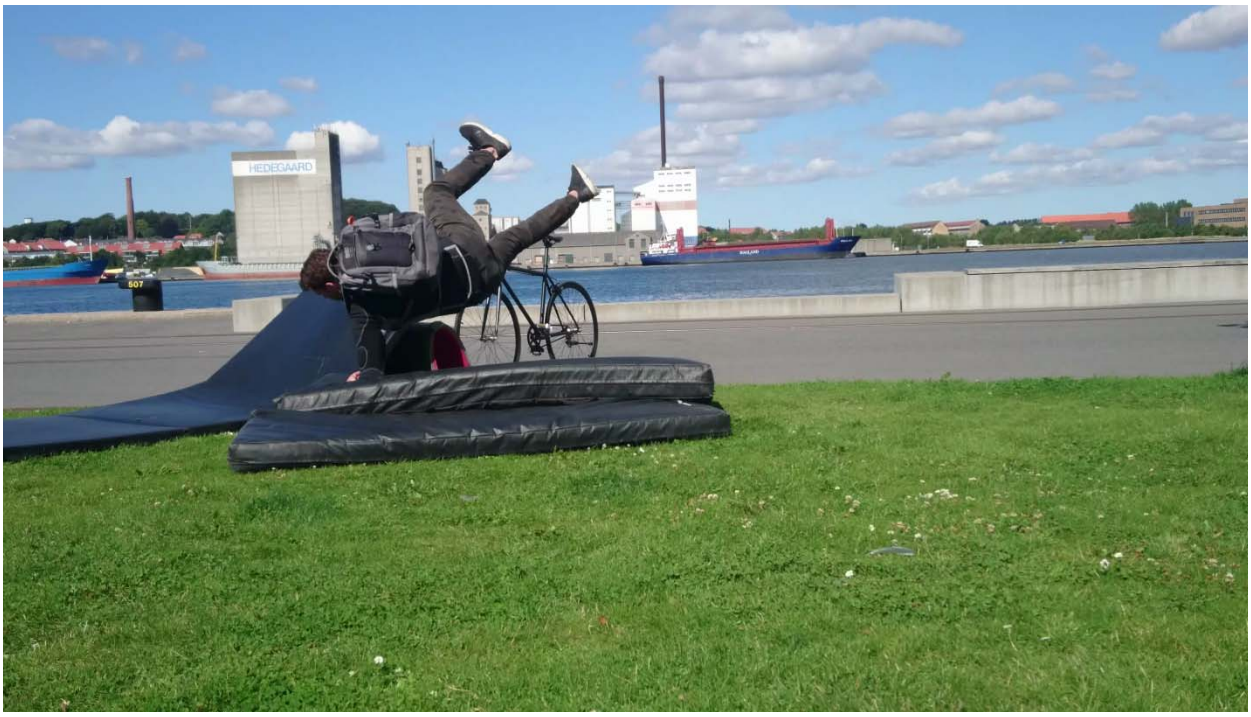


Figure 5: A stuntman performing simulated accidents. Example: https://youtu.be/ASm97EJM60c

Accident types 1-3 and 5 were simulated using a crash test dummy: 1) forward cycling falls (type 1) with the phone placed in the chest pocket (5 cases); 2) sideways cycling falls (type 2) with two different sensor locations: chest pocket (10 cases), trousers pocket (10 cases); 3) forward pedestrian fall (type 3) with the phone placed in the trousers pocket (10 cases); 4) backward pedestrian falls with the phone placed in the chest pocket (5 cases) and with the phone in the trousers pocket (5 cases). In total, 45 simulated accidents were performed using the crash test dummy. During the cycling accident tests the dummy was mounted on a bicycle which was then pushed into an obstacle/curb with a speed of approx. 15 km/h. For the pedestrian forward falling accidents, the dummy was carried by two research staff that simulated to stumble over an obstacle and dropped the dummy. For the pedestrian slipping and falling backwards, the dummy was rolled forward in walking speed on a low table with wheels and the table was suddenly kicked forward.

Besides the dummy crash tests, the event picking up the phone abruptly from the chest pocket (10 cases) and from the trousers pocket (10 cases) were recorded to be able to discriminate crash events from “normal” phone usage. All the test situations were videotaped the clock on the video recordings was calibrated against the clock of the sensor app in the smartphone.

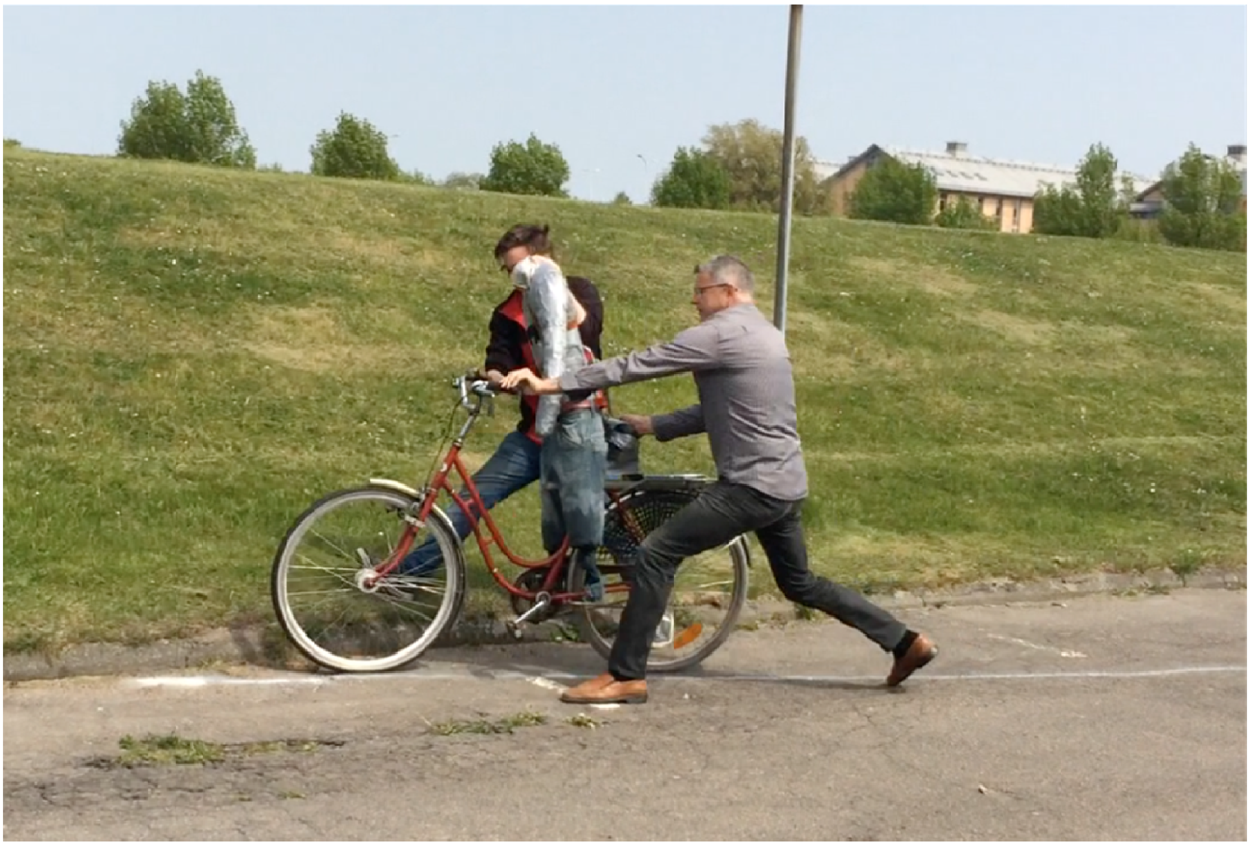
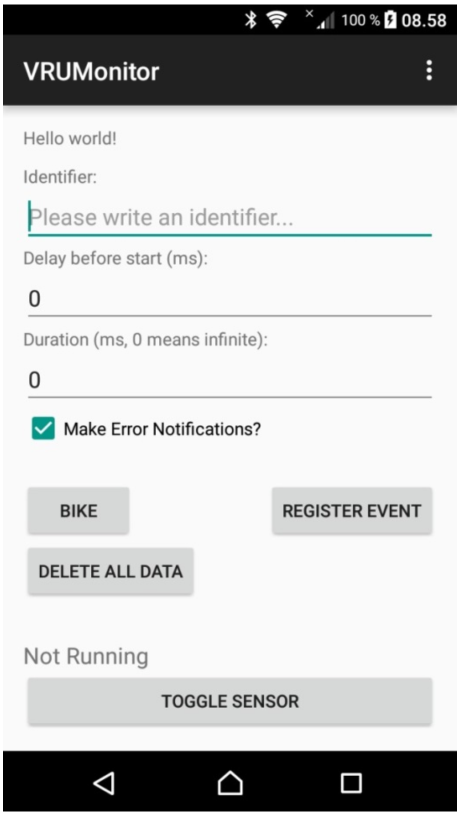


Figure 6: Simulating sideways cycling accident with a crash test dummy.

In addition, normal cycling and walking data from daily commute was collected with various sensor locations.

Motion data was collected from an Android smartphone with an app which was developed specifically for the study (Figure 7). The app recorded acceleration (three axes), rotation (three axes) and the screen state (turned on/off) with a sampling rate of approximately 5 Hz. The latter indicator, i.e. the screen state, was recorded to be able to discard movement from picking up the smartphone and using it. Samsung Galaxy S6 smartphones were used in the accident simulations. A Sony Xperia Z5 Compact was used for collecting normal cycling and walking data.



Hello world!

Identifier:

Please write an identifier...

Delay before start (ms):

0

Duration (ms, 0 means infinite):

0

☑ Make Error Notifications?

Not Running

Figure 7: Data collection app

4.2. Rule-based accident detection

A rule-based algorithm was developed to detect accidents based on kinematic triggers (acceleration, rotation and jerks). Furthermore, changes in the state of the screen (turned on/off) were monitored and used for reduction of the number of false triggers when handling the phone.

4.2.1. System design

An Android application was designed based on the above criteria. The acceleration sensor of the phone was used to measure the acceleration and jerk and the gyroscope sensor to measure the rotation of the device. The app runs in the background and continuously monitors any changes in acceleration, jerk, and rotation. The underlying logic of the detection part of the application is shown in Figure 8.

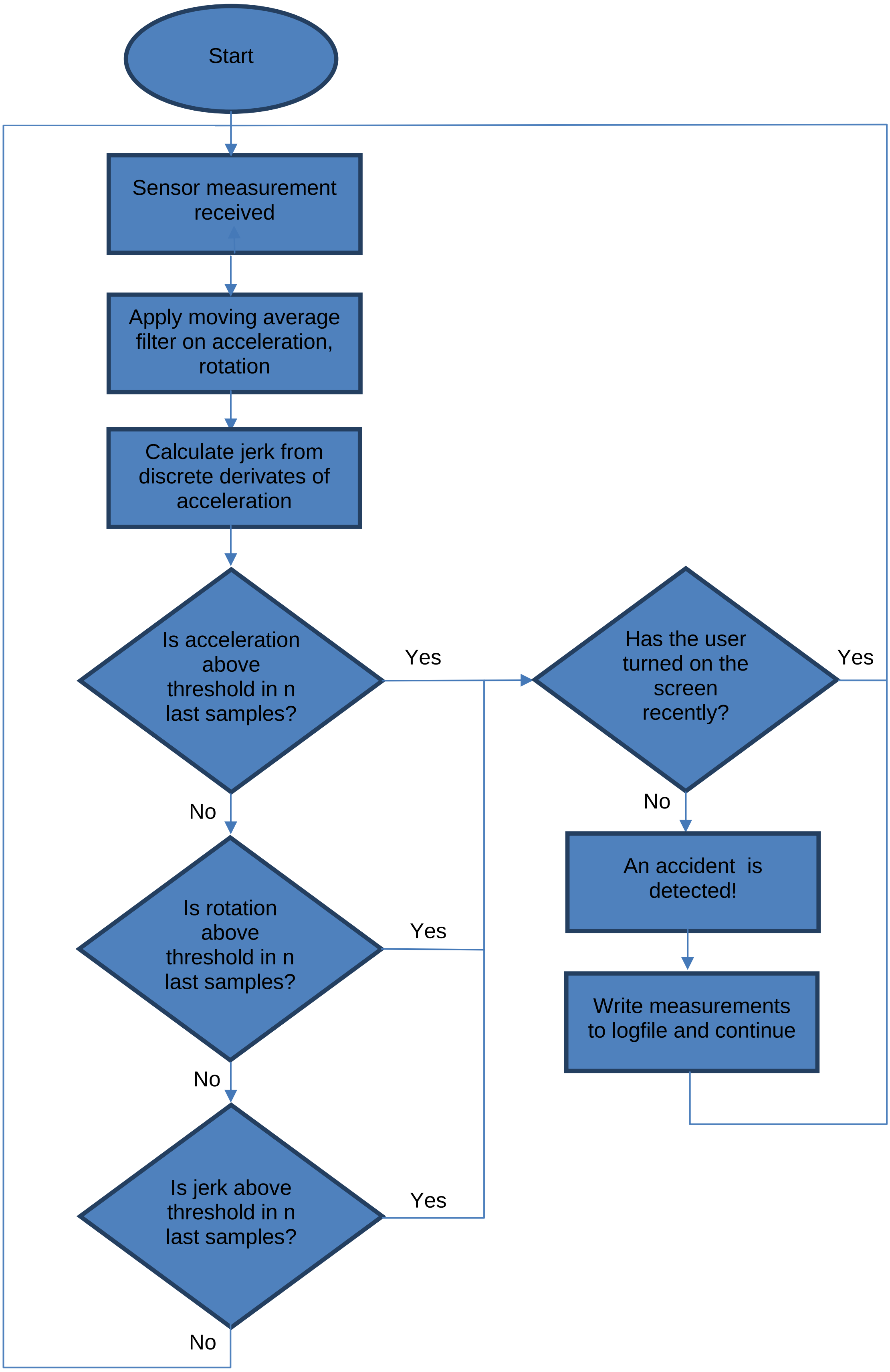

Start
Sensor measurement received
Apply moving average filter on acceleration, rotation
Calculate jerk from discrete derivates of acceleration
Is acceleration above threshold in n last samples?
Yes
No
Is rotation above threshold in n last samples?
Yes
No
Is jerk above threshold in n last samples?
Yes
No
Has the user turned on the screen recently?
Yes
No
An accident is detected!
Write measurements to logfile and continue

Figure 8: Flow diagram of the rule-based detection application. The time window (n) and the different thresholds were found manually.

4.2.2.Results of tests on simulated accidents

The rule based algorithm could detect 14 out of 14 dummy accidents and 23 out of 35 stuntman accidents (Table 1). This difference was caused by the characteristics of the two methods of simulating accidents; while the crash test dummy does not move its limbs, and cannot stop the fall, the stuntman arranges himself in a way to reduce the impact when hitting the ground and makes the difference in motion patterns between normal behaviour and accidents less obvious.

Table 1: Simulated accidents detected by using rule based approach

	Detected	Not detected
Stuntman	23	12
Dummy	14	0

Figure 9 shows an example of the magnitudes of the acceleration and rotation measured in a simulated accident of a cyclist falling sideways. In the dummy simulation, the dummy was brought up to speed starting from a few seconds before the measurements were initiated. The last part of the acceleration to reach cycling speed is seen, followed by the fall (after 4 s) and the moment after the fall where the dummy is left on the ground. A large peak is seen in both acceleration and rotation where the dummy hit the ground. The acceleration peaks at approx. 38 m/s^2.

A similar fall was simulated by the stuntman. The phone was placed in the chest pocket and then the stuntman accelerates. After 5 seconds he hits the obstacle and falls onto the mattress, rolls onto his side, stands up and takes the phone out of the pocket to turn off the data collection. This results in a small peak in the end. No peak is observed in the acceleration or rotation at the moment of the fall, but generally, more motion is registered throughout the whole simulation.

A peak could not always be seen in the stuntman data at the time of the fall and in case that there was a peak, it was smaller than that of the dummy. While the crash test dummy falls to the ground without being able to cushion the fall, the stuntman will, on the other hand, prepare for the fall and do what he can to avoid injuries. The peak in some simulated accidents but not in others may be a result of how the stuntman succeeds in breaking the fall. The impact when hitting the ground will thus most likely be higher in a real accident than shown in the stuntman data but potentially lower than reflected by the dummy data, as the road user will try to cushion the fall.

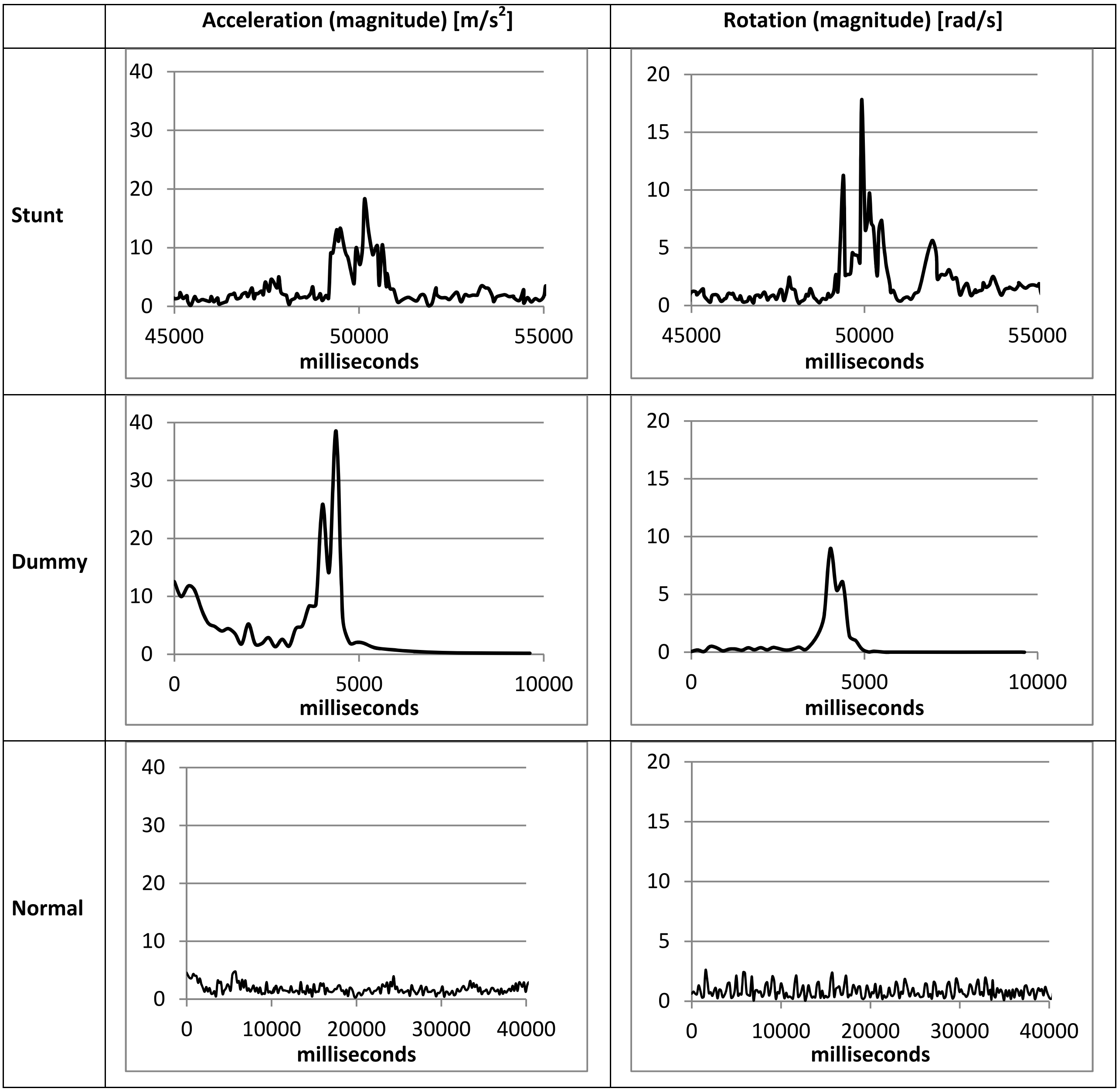
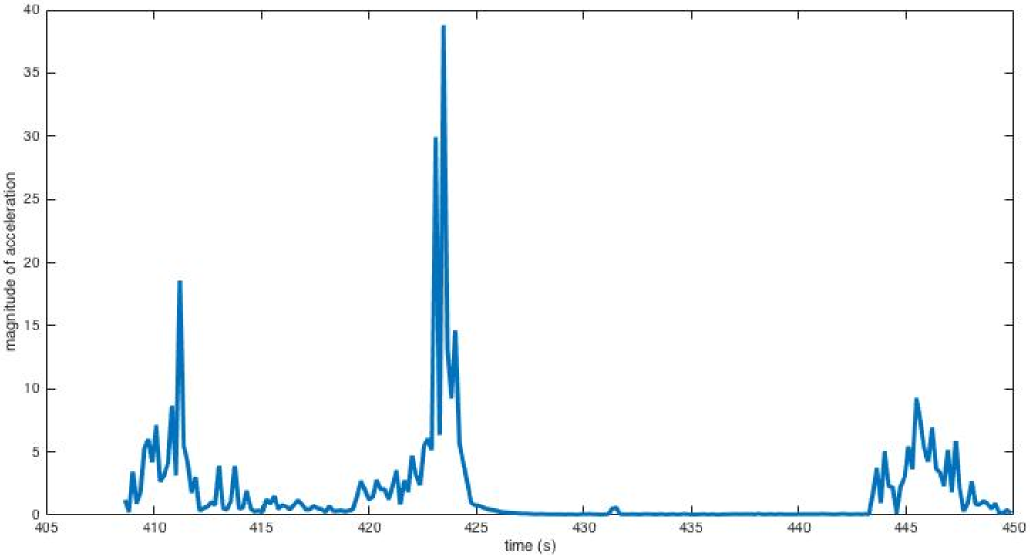


Figure 9: Example of motion data from stunt and dummy accident simulation (sideway cycling fall, phone in chest pocket) compared to normal cycling data (phone in jacket inner chest pocket).

4.3. Machine learning system

A machine learning algorithm, based on logistic regression, has been designed with the purpose of discriminating accidents from normal use based on accelerometer and gyroscope data collected from a mobile phone. From the experiments the conclusion is that the best cue to use is the accelerometer data. An example of the data used is shown in Figure 10. The x-axis shows the time in seconds, and the y-axis shows the magnitude of the acceleration. At the start (at around 410) the bicycle is accelerated manually towards its target accident. At around 420 to 425 seconds one can see the acceleration during the actual accident. The final peaks at around 445 seconds are due to the bike being picked up. In Figure 11 several accidents after each other can be seen. A similar pattern is apparent.



Figur 10: Example of acceleration data from one bike accident. The graph shows the initial acceleration of the bike, the crash and the final pick-up of the bike after the accident.

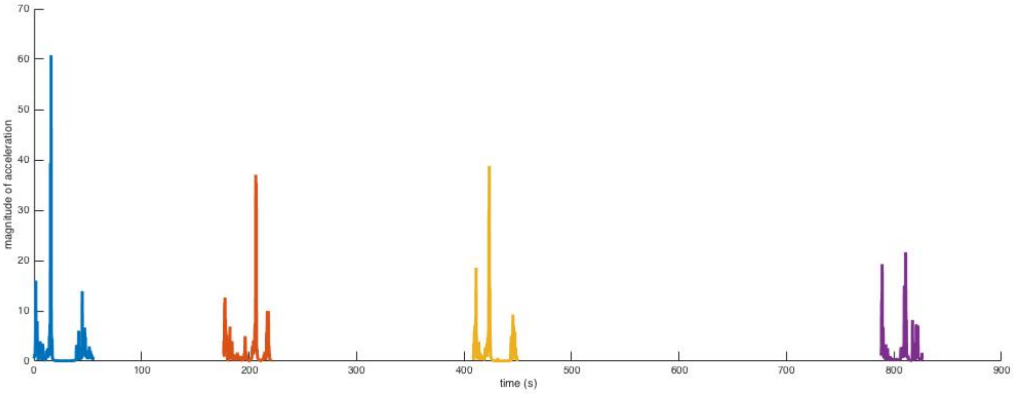


Figure 11: Example of accelerometer data from four different accidents.

The aim and focus has been to localize the event in time, not only to detect that it had occurred. The features used in this method were based on the magnitude of the measured accelerometer vector. For each time instance a small time-window of measurements is extracted. All the measurements are then interpolated within this time window to a fixed time resolution that allows getting a fixed length feature vector. Using a manually annotated ground truth a trained classifier based on logistic regression is learned. Since the amount of available training data was limited, a classic classification method was selected to avoid overfitting.

In Figure 12 the result of running the classifier is illustrated. The classifier was trained on half the data and tested on the other half. The result is shown in the figure. The resulting classification for each time instance is shown, and it is clear from the results that all the accidents can be detected successfully, without any false alarms on the normal data. Furthermore one can see from the overlap with the ground truth that a good localization of the accidents is achieved as well.

The system was trained and tested on limited data and therefore no final conclusions can be drawn - more work is needed- especially on multiple phones, which turned out to be a challenge in the rule-based system. But these initial results show the feasibility of detecting accident using only the input of accelerometer data.

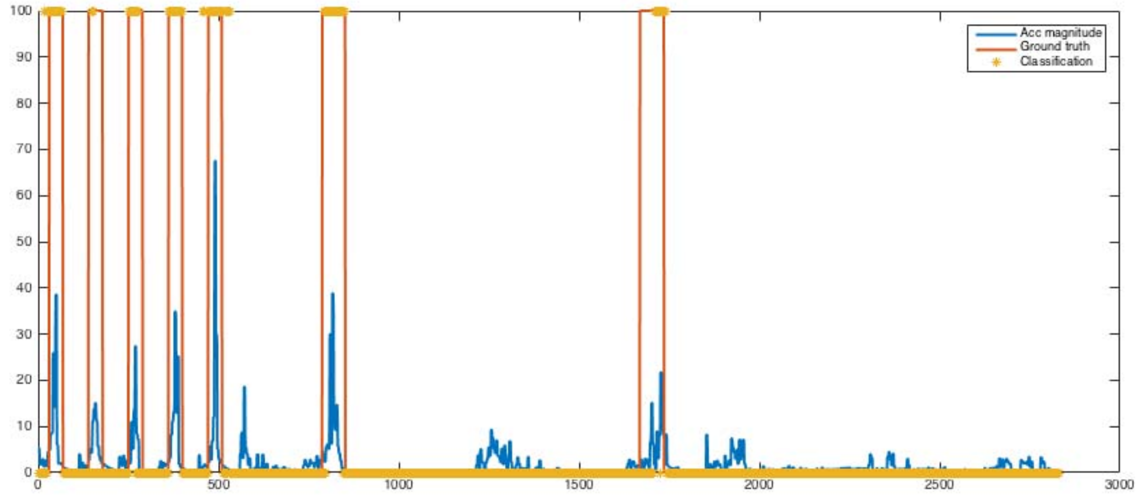


Figure 12: Example of classifications vs ground truth data.

5. Discussion and Conclusions

The notion of using technology to aid the data collection process is sound. The alternative requires too much manual labour. In this report the focus has been on using technology to increase the knowledge about VRU via smartphone apps. This approach first requires a backbone database with software tools for generating and managing questionnaires. Such a system has been successfully developed and used to handle more than 11,000 participants.

A smartphone app was developed to automatically detect ccidents by analysing the motion data on the phone. The underlying idea is that accidents result in abnormal movement compared to everyday activities and hence by analysing movements, accidents can be detected automatically. Realistic training data was collected using a stuntman and a dummy doll. Both a simple rule-based approach as well as a more advanced machine learning approach were developed and tested. It seems that accidents can be predicted by rule-based or learned models, but fails to generalize across devices since different motion sensors on different smartphones react differently and require tedious individual calibration. It was therefore decided not to ask participants to download and implement the developed apps. Instead a smartphone app was developed for self-reporting. This app was used by more than 400 participants resulting in a large amount of data that are currently being analysed. It is expected that this data will result in valuable insights into VRU and accidents.