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# Learning for sensor-based, real-time fall detection for cyclists.

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of the requirements for the degree of  
B. A (Mod.) Computer Science

# Declaration

I hereby declare that this project is entirely my own work and that it has not been submitted as an exercise for a degree at this or any other university.

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# Abstract

Like all extreme sports, mountain biking comes with the potential for serious injury to the rider in the event of an accident. Non fatal injuries can easily become fatal, when one is alone, far from help and potentially incapacitated. A study conducted by Paracelsus Medical University recorded injury rates as high as 16.8 injuries per 1000 hours of riding, with 22 being moderate and 16 being severe, with rider error being the leading cause (1). An automated crash detection system has the potential to be life saving in the worst of circumstances.

Existing discipline-specific solutions e.g., for road only or for mountain use only, on both hardware (Specialized's AnGi) and software (Strava Beacon, Garmin) have inflexible detection algorithms focusing on using thresholds for only one to two data points. For example AnGi records values from its inbuilt gyroscope and accelerometer, while Garmin's system uses only accelerometer values. Such threshold-based solutions pose issues in terms of high false detection rates and a single threshold value is unlikely to be suitable for different users at different skill levels.

This project expands on previous research done in the area of wearable fall detection devices for the elderly, focusing on the design of a software solution for real-time fall detection. Three data points are used: raw sensor data from both a tri-axial gyroscope and a tri-axial accelerometer as well as the rate of change of speed, calculated via GPS. The proposed system utilizes learning techniques to improve detection rates and over time generates a more personalized model. Based on pre-captured training data of both regular riding and crashes, data is classified using a multivariable logistic regression model in real-time to determine whether a crash has occurred. Raw sensor data is captured from the inbuilt sensors present on android smartphones.

This approach is implemented as an android application called "RideSafe" and was evaluated using a user study, comprising of X participants at local trail centres over a Y day period. Crash data was also collected, by means of intentional crashes in a controlled environment for verification. Results show that this system can successfully detect upwards of X crashes with a low rate of Y false positives. . . .

# Acknowledgements

Thanks Mum!

You should acknowledge any help that you have received (for example from technical staff), or input provided by, for example, a company.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Motivation . . . . .	1
1.2	Aims . . . . .	1
1.3	Personal Goals . . . . .	2
1.4	Readers Guide . . . . .	3
<b>2</b>	<b>Background</b>	<b>4</b>
2.1	The Concept . . . . .	4
2.2	Exsisting Solutions - Medical . . . . .	5
2.2.1	Vision Based Approaches . . . . .	5
2.2.2	Sensor Based Approaches . . . . .	5
2.3	Exsisting Solutions - Cycling . . . . .	6
2.3.1	Garmin . . . . .	6
2.3.2	Specilized's ANGI . . . . .	7
2.4	Threshold based solutions . . . . .	7
2.5	Supervised Machine Learning . . . . .	8
<b>3</b>	<b>Evaluation</b>	<b>9</b>
<b>4</b>	<b>Conclusion</b>	<b>10</b>
<b>A1</b>	<b>Appendix</b>	<b>12</b>
A1.1	Appendix numbering . . . . .	12

# 1 Introduction

## 1.1 Motivation

Personal experiences were the main driving factor in my motivation to pursue this study. As a mountain biker with 10 years of experience I have sustained my fair share of minor injuries, but witnessing injuries sustained by more venerable fellow riders are sometimes more impactful. Last summer on a seemingly normal spin with a friend, we discovered a woman lying injured off on the trail side, incapacitated and unable to call for help so I did on her behalf. Multiple phone calls later to aid the first responders in locating us they arrived - around 1 hour after impact. This experience made me realize how useless your mobile phone is to you in these situations when one is unable to even pick it up. Non fatal injuries can easily become fatal, when one is alone, far from help and potentially incapacitated.

## 1.2 Aims

The aim of this project was to develop an android application for real-time fall detection for cyclists, automating the process of requesting assistance, and to reduce response time in the event of an accident. Before development of the application I set myself strict aims to achieve.

### **Simplistic and Intuitive**

After the initial set up process, to carry out the main use case: crash detection would be started and stopped with a single press of a button. Start the service, put your phone in your pocket and enjoy your time on you bike with piece of mind. Simple and convenient to use, removing the possibility of confusion for the end user, as the end users will be members of the general public. A simple user interface is important as the setting to which the app would be outdoors in potentially harsh weather conditions, external factors such as glare from the sun and the possibility of moisture on the screen make high detailed, small user interface elements unsuitable. Less is more in this scenario.

## **Diverse**

Many existing systems are discipline specific, only working for one aspect of cycling i.e., for cross country usage only. I intend this app to have the potential to work for all disciplines of cycling. Targeting single disciplines would drastically reduce the number of potential users as well as producing highly undesirable, inaccurate results if used for the incorrect discipline.

## **Standalone**

Utilizing android smartphones built in sensors removes the need for extraneous external equipment for ride monitoring. I intend the app to work as expected with one's phone placed in their pocket or bag, requiring no extra mounting equipment for either the rider or the bike.

## **Enjoyable user experience**

Many existing solutions exhibit deal breaking issues which ultimately causes the end user to stop using the system, I aim to eradicate the pitfalls present in other systems leading to a better user experience.

## **Efficiency**

Performance in terms of battery usage is of utmost importance, heavy battery usage would have the potential to kill the phone when one would need it most - in an emergency. Every possible optimization in terms of battery will be made where possible - without impacting performance.

# **1.3 Personal Goals**

In addition to the aims of this project I had set some personal goals to achieve from undertaking this project.

## **Develop a fully functional application.**

Having had brief experience working with android studio before undertaking this project to develop simple applications, most of which were interfaces for arduino circuits connected via bluetooth, I had never developed such a large scale complex application prior to this project. I was excited to broaden my skill set and develop an application ready to be published to the google play store.

## **Work with Embedded sensors.**

Having experience working with microcontrollers and various sensors, I was excited to utilize the plethora of available sensors present in android smartphones today.

## **Collect and Analyse Real World Data.**

Datasets for what a bike accident looks like in terms of sensor values are few and far between, I was excited to conduct my own research with many unknowns to which I would need to discover. Having very few similar documented studies available I was very interested to study this particular system in the domain of cycling.

## **Real world testing.**

I was aware before undertaking this study that it would involve a lot of real world data collection, analysis and testing. Being a crash detection application testing could not be simulated sitting at a desk, which meant all my testing would need to be done in the real world which proved both challenging and exciting.

# **1.4 Readers Guide**

## **2 - Background**

This section will discuss the concept of fall/accident detection, exploring both the sport and medical applications. The two main approaches of fall detection will be discussed and the strong points as well as issues with each type of system will be discussed.

## **3 - Design**

here about design

## **4 - Implementation**

here about implementation

## **5 - Evaluation**

evaluation goes here

## **6 - Conclusion**

da CONCLUSION



## 2 Background

Accidental falls and accidents resulting in injury is a large scale world wide problem, A study conducted by the American Journal of Public Health found that the leading cause of death is falling, for people aged 50 or above, a 136% increase over a 30 year period(2). Accidents are not aged biased however certain sports come with a higher probability of accidents occurring. Like all extreme sports, mountain biking comes with the potential for serious injury to the rider in the event of an accident. In 2018 there were 29,000+ registered members of cycling Ireland in over 450 clubs (3) , with this number set to increase year on year. With an increase of the number of people taking up the sport, the amount of reported injuries has also increased significantly. A study conducted by Paracelsus Medical University recorded injury rates as high as 16.8 injuries per 1000 hours of riding, with 22% being moderate and 16% being severe (1). The most common mechanism of acute severe injury for mountain bikers has been found to be falling forward (64.9%), which lead to the most severe injuries, with an ISS <sup>1</sup> of 3.4 out of a possible 6 (currently untreatable ) (4)

Existing solutions for fall detection for both medical (Fall detection for the elderly) as well as existing crash detection systems for cyclists will be discussed and explained in this chapter.

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<sup>1</sup>Injury Severity Score

## 2.1 The Concept

Fall detection for the elderly has been around for decades, the original idea came to fruition as a result of the impracticality of having around the clock care for the independent, but fragile members of society. With high success rates and the advancement of technology in recent years the concept has been applied to many different uses cases, such as accident detection in vehicles and sports.

## 2.2 Existing Solutions - Medical

Fall detection is not a new concept in the medical domain, The first fall monitoring system (PERS<sup>2</sup>) Hausnotruf was developed in the 1970's by Wilhelm Hormann These early active systems were manually triggered, requiring the user to activate them by pressing a button on a transceiver, while relying on an active phone line in the home to contact help. Active systems have been mostly phased out due to their main weakness - the user must be conscious and capable of triggering the alarm. Passive systems are now commonplace and most relevant to this study. Passive systems monitor the users movement and trigger the alarm without the need for user interaction with the system. Passive systems can be implemented in one of two ways: Vision Based approaches and wearable sensor based solutions. Currently Sensor based solutions are widely available, while computer vision implementations are mostly experimental proof of concepts.

### 2.2.1 Vision Based Approaches

Computer Vision Approaches are currently the state of the art in terms of fall detection for the elderly, these systems comprise of multiple cameras set up in the home, with a base station analysing the video footage to determine if the user is in need of assistance.

Implementing Computer Vision techniques such as optical flow or Gaussian Mixture Models, to focus on moving objects and ignoring the background, allows for recognition of falls or slips. Many environmental issues such as changing lighting and limited view of cameras in the home impede the accuracy of these systems. Unfortunately for these systems it isn't possible to constrain the environment enough to allow for near perfect accuracy. Vision based approaches also pose a large risk to the occupants privacy. 24/7 surveillance in the home is not something anyone desires, especially in what is supposed to be the comfort of your own home. Depending on the security utilized, vulnerabilities may exist exposing the stream to the world.

Cost is a large factor in why sensor based solutions are preferred, the cost of initial setup is

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<sup>2</sup>Personal Emergency Response System

much higher for a computer vision solution. Adding complexity to an implementation while simple more effective solutions, with similar or in some cases better results is a step in the wrong direction.

## **2.2.2 Sensor Based Approaches**

Wearable sensor based solutions are very common globally, in both passive and active products. These wearable devices are usually in the form of a small external device.

These devices can be:

- wrist mounted
- attached to a belt
- pendant worn around the neck.

Housed within these enclosures are embedded sensors, the most common of which is the triaxial accelerometer. The triaxial accelerometer measures proper acceleration in 3 perpendicular axis (g-force). Almost every wearable fall detector factors in accelerometer values while determining if a fall has occurred or not. The second most common sensor used in fall detection is the triaxial gyroscope, used to calculate rotational speed. Gyroscopes have proven to be useful for understanding the direction of a fall. Depending on where the device is worn, some false positives which would occur using only an accelerometer can be disregarded, such as sitting down too quickly. A pendant style device's relative rotation would be more or less unchanged sitting down vs standing. The use of highly sensitive barometric sensors have also been utilized to measure minute changes in atmospheric pressure, the difference between pressure when one is standing vs lying down can be distinguished between. The most popular commercially available fall detection using barometric sensors is lifeline (5). There is no standard passive implementation, solutions include one or more of the above sensors along with an algorithm or formula to determine if a fall has occurred.

## **2.3 Existing Solutions - Cycling**

Todo

### **2.3.1 Garmin**

Garmin, best known for producing GPS based navigation systems, include incident detection with their cycle computers Edge 1030 and above. Garmins incident detection is one of the most basic solutions available on the market today - A simple threshold based system using

only a Gyroscope for detection. “ Incident detection should not be relied on as a primary method to obtain emergency assistance. “ - Garmin. Incident detection is for road use only resulting in it being next to useless for a large percentage of their customers - mountain bikers. Garmin cycle computers are very expensive, however they perform their main intended use (Navigation) to an excellent standard. The limitations of systems such as this will be discussed in (link to threshold) to threshold based solutions.

### 2.3.2 Specilized's ANGI

In late 2018 Specialized released their crash detection solution - ANGI <sup>3</sup>, (6) building upon technology acquired from icedot in 2017 (7).

ANGI is a threshold based system comprising of three components:

- Compatible Helmet
- ANGI Sensor
- Smartphone

The ANGI sensor is a small device which mounts to the rear of a compatible helmet, consisting of a bluetooth chip, an accelerometer and a gyroscope. While connected to a compatible smartphone ANGI measures linear and rotational forces present at the riders helmet. When a crash is detected the users mobile phone is used to contact an emergency contact. The ANGI sensor is relatively inexpensive on its own (euro50), but factoring in the cost of a compatible helmet and the yearly subscription fee (alike many medical solutions) the solution becomes less budget friendly. Utilizing external sensors like ANGI allows for consistent placement relative to the rider, but utilizing bluetooth connectivity adds an extra step needed to use the device as well as introducing latency and reliability concerns.

## 2.4 Threshold based solutions

Most simple sensor based implementations are threshold based, meaning they compare current sensor readings to a predefined threshold value at a given moment in time. If the current value(s) surpass the threshold(s) a fall or crash will be flagged. This simple implementation focuses solely on a single value from a single point in time, context of what the previous value or the next value is not taken into account, as previously mentioned before garmins incident detection uses this implementation. Threshold based solutions work quite well for medical applications, thresholds are actually quite suitable for slow moving humans wandering around a home, very few daily tasks would surpass a threshold set for

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<sup>3</sup>ANGI - Angular and G-Force indicator

falling over. The forces experienced from daily tasks have been shown to be far lower than what is experienced during a fall for instance ( reference something)

For the application of mountain biking, there are three main reason to why a threshold based solution is not the optimal solution:

- Tend to be discipline specific:

To compute a single threshold for multiple disciplines of cycling is infeasible, the forces experienced during a commute are on average far lower than what is experienced while mountain biking. A system intended for road use only would trigger seconds into a mountain bike trail. (maybe image of trail beside road).

- Unsuitable for different riders of different skill levels:

With cycling in general, as the riders skill and experience increases , their speed also increases resulting in higher forces experienced. (slow vs fast same trail graph ) Single threshold values are unsuitable among different riders and will produce poor results.

- High rate of false positives:

Accidental non crash actions such as dropping the device, or shaking it rigorously can easily fool a threshold based systems ( \*\*\*\*\*See car park test \*\*\*\*\*) . false positives can have serious legal repercussions if the system is programmed to contact the local emergency services, potentially diverting limited resources away from a true emergency.

## 2.5 Supervised Machine Learning

## 3 Evaluation

## 4 Conclusion

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# A1 Appendix

You may use appendices to include relevant background information, such as calibration certificates, derivations of key equations or presentation of a particular data reduction method. You should not use the appendices to dump large amounts of additional results or data which are not properly discussed. If these results are really relevant, then they should appear in the main body of the report.

## A1.1 Appendix numbering

Appendices are numbered sequentially, A1, A2, A3. . . The sections, figures and tables within appendices are numbered in the same way as in the main text. For example, the first figure in Appendix A1 would be Figure A1.1. Equations continue the numbering from the main text.