Mitigating motorcycle accidents at yield junctions using Computer Vision and Deep Learning: a preliminary study

Simon McCool PhD Student (Final Year)

Supervisor team: Prof. Volker Steuber, Dr Wei Ji and Dr Christoph Salge

University of Hertfordshire UH

Overview of this presentation

- Research Aim
- Motivation
- Current research into causality
- Research questions raised so far
- Methods to address some of the research questions raised
- Preliminary results on synthetic input data
- Next steps: Live experimentation

Research Aim

This research aims to exploit pixel-level data from 2d video, to create feature vectors linking prior behaviour and intent of vehicle drivers.

Leading to an intent prediction at a junction.

Objective:

To predict driver intent at yield junction to mitigate motorcycle accidents

Why: “An accurate prediction of future trajectories could further mitigate the severity of a collision. “

How: Two main methods combined into a framework:

1. An intent prediction classification framework: To classify threats based on prior behaviours
2. A real-time object detection, tracking, and intent prediction algorithm dynamically predicting intent.

Motivation

Accidents involving motorcycles are significantly higher at un-signalised junctions [1].

Current research into causality

“Look But Fail To See" (LBFTS) errors.

“..genuine fixation errors without perception, rather than a failure to fixate or a failure to appraise” [2]

In another study evidence suggests that drivers accept smaller gaps at junctions in front of motorcycles compared to cars. [3]

Driver education is the accident mitigation route in many studies.

Accident mitigation using onboard technology

Automatic emergency braking system for motorcycles (MAEB)

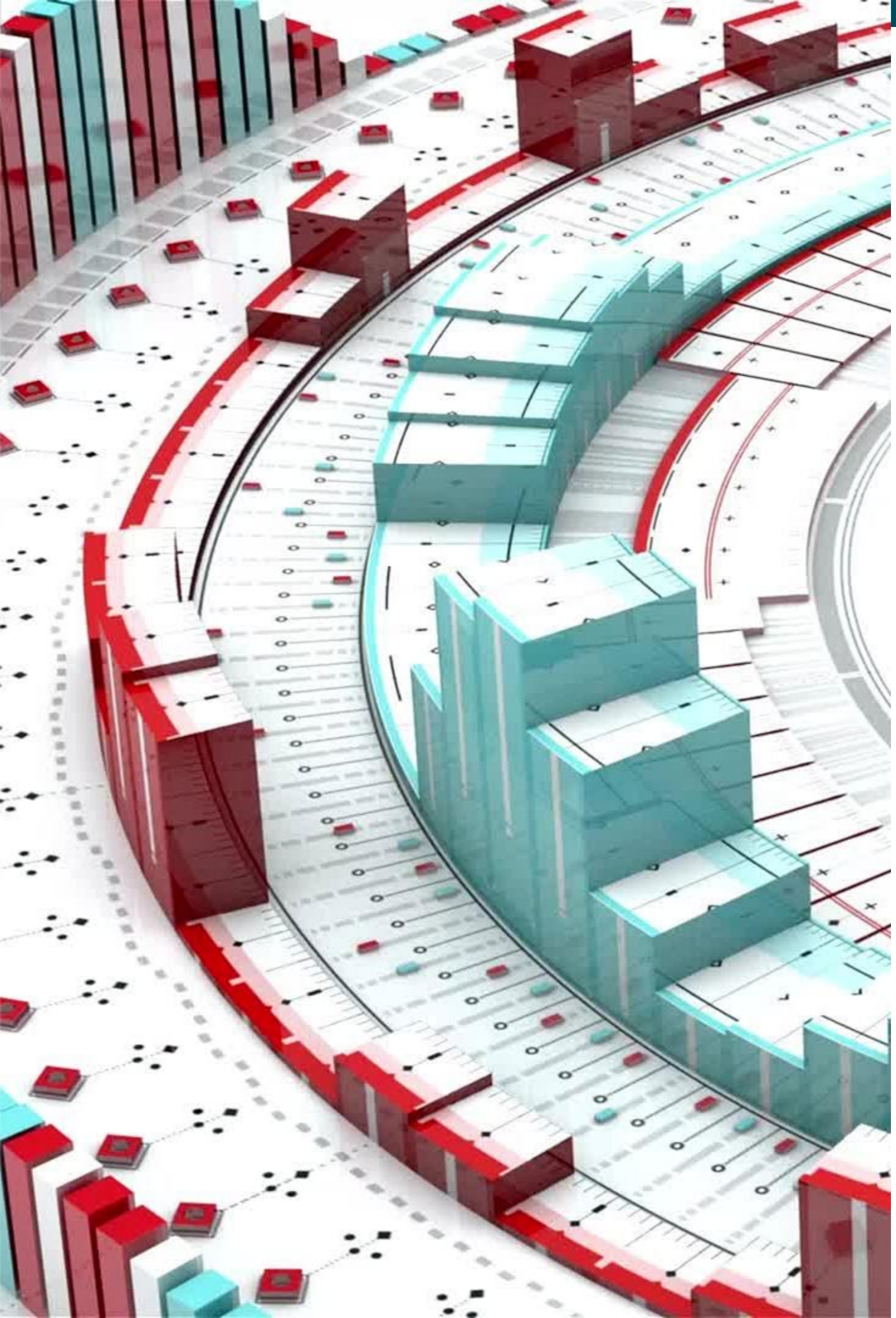
The speed reduction at impact produced by MAEB could potentially mitigate the crash severity for the riders. [4]

However, the inevitable collision state used for the triggering intervenes less than 0.4 s before the actual collision. [5].

At 0.4s to impact the vehicle is already in front of the motorcycle.

Research Questions

- What empirical behavioural features an exhibited by drivers approaching a junction?
- What are the acceleration characteristics of a non-yielding driver at variable distance intervals before a junction?
- Can vehicle driver intent be predicted in real-time?
- What pixel-based kinetic features reveal driver behaviour?
- How can simulated traffic acceleration profile vectors be processed into a training dataset?
- Can synthetic data be augmented into a dataset without compromising the performance of the ML model
- Can driver intent be classified using a feature vector-based dataset?
- How does reducing object classes in training data affect inference accuracy and performance?
- What hyperparameter tuning values results in an improved inference rate without degrading accuracy?



Methods

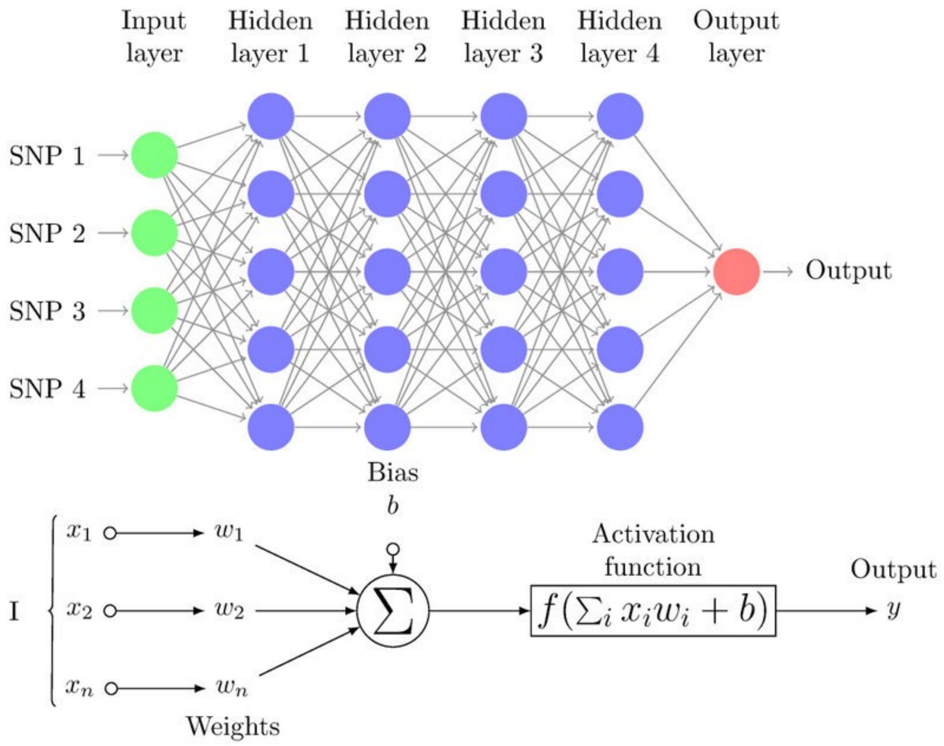
Data collected from live traffic observations and simulator environments.

Two methods, described as Daisy and Duke:

Daisy is a linear classification method trained on empirical data

Duke is a real-time algorithm that ingests and analyses data from live video frames

Method: Daisy a Linear Classifier



Uses a dataset of generated predictions and empirical observations.

A simple linear classifier which analyses inputs and attempts to determine an outcome based on behaviour.

DATA: Acceleration profiles at distances, outcomes at junction, velocity and distance from junction. SNP1-4

Empirical data from live observations of vehicle behaviour at yield junctions

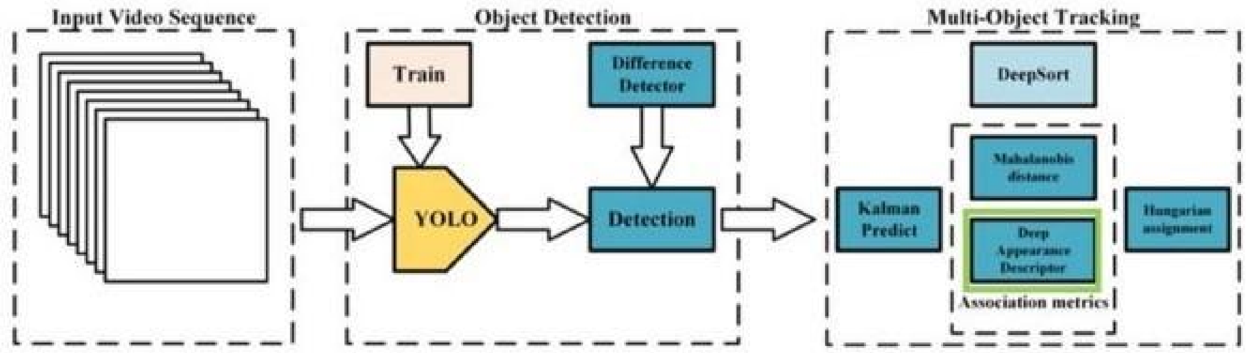
Data from Duke

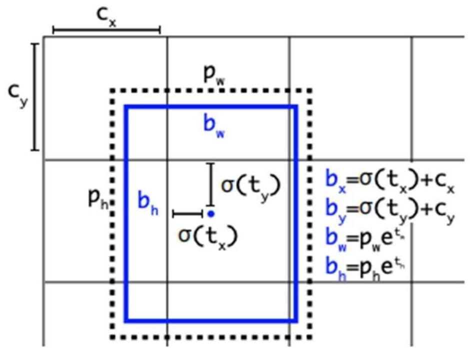
Training. Ongoing training as we collect more data

Method: Duke Real time inference and intent prediction 1

The objective is to leverage the performance of single-shot detector and DL tracking algorithms

- Input is in 2D video passed to YOLOv5 for object detection
- Data is then passed to DeepSORT as a feature vector
- Our algorithm, Duke, ingests vector data and analyses the differential values to predict if the vehicle will yield at the junction or carry on and enter the main road.





$$b_x = \sigma(t_x) + c_x$$
$$b_y = \sigma(t_y) + c_y$$
$$b_w = p_w e^{t_w}$$
$$b_h = p_h e^{t_h}$$

YOLOv5 predicts four coordinates for each bounding box

Creating the framework

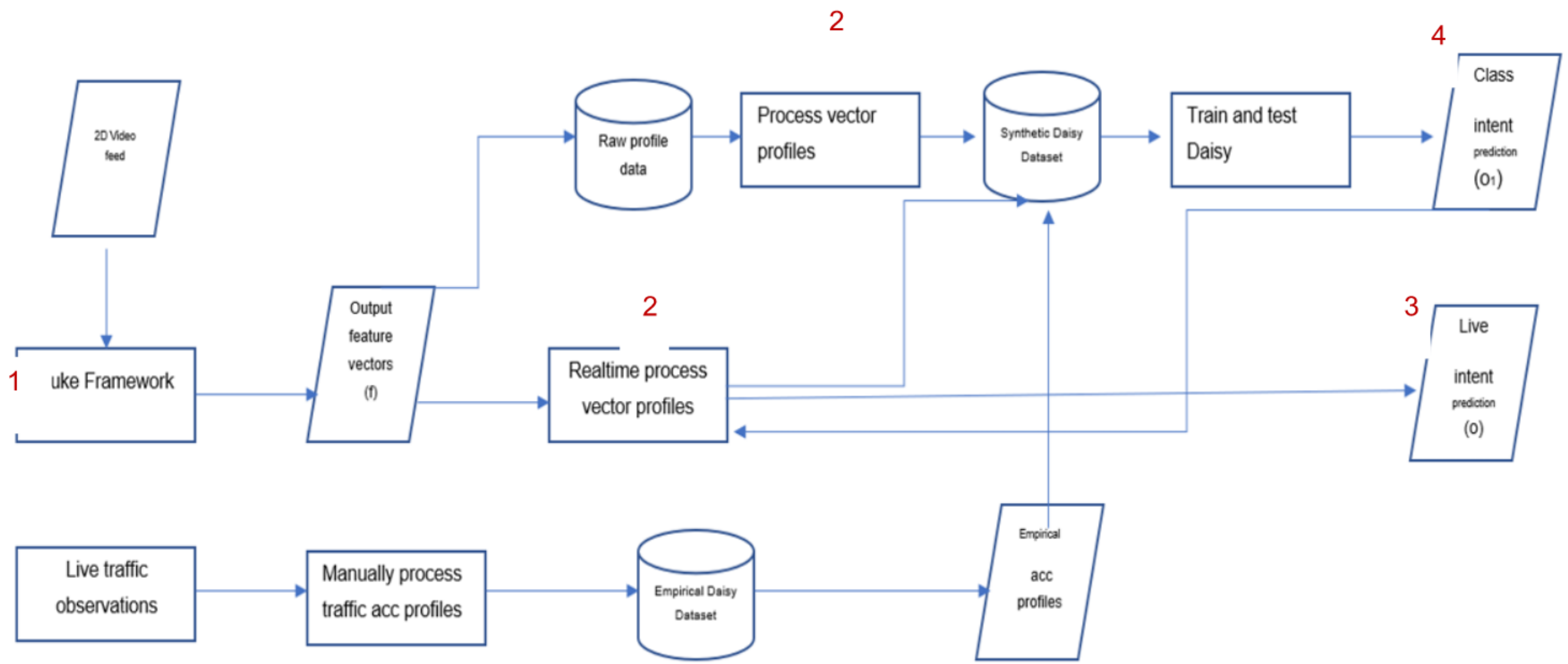


Figure 2. Framework and pipeline incorporating both methods for intent prediction have four main components.

1. *Object detection and tracking*
2. *Object analysis and feature vector extraction from 2d video*
3. *Live Intent prediction (Duke)*
4. *Intent classification (Daisy)*

Method: Duke Real time inference and intent prediction 2 (Dataset)

Objective: Training a more realistic system with limited field of view in terms of angle and range[6]

This means creating a handcrafted dataset focusing only on the right-hand side and front of vehicles,

Minimises triggering an intent prediction on a false positive threat.

Raw image

Processed image

Results Daisy:
Using a confusion matrix as an alternate method for the performance of the whole model, we get an accuracy of 0.89.

N=66	PREDICTED YIELD	PREDICTED NO YIELD
Actual yield	37	3
Actual no yield	4	22

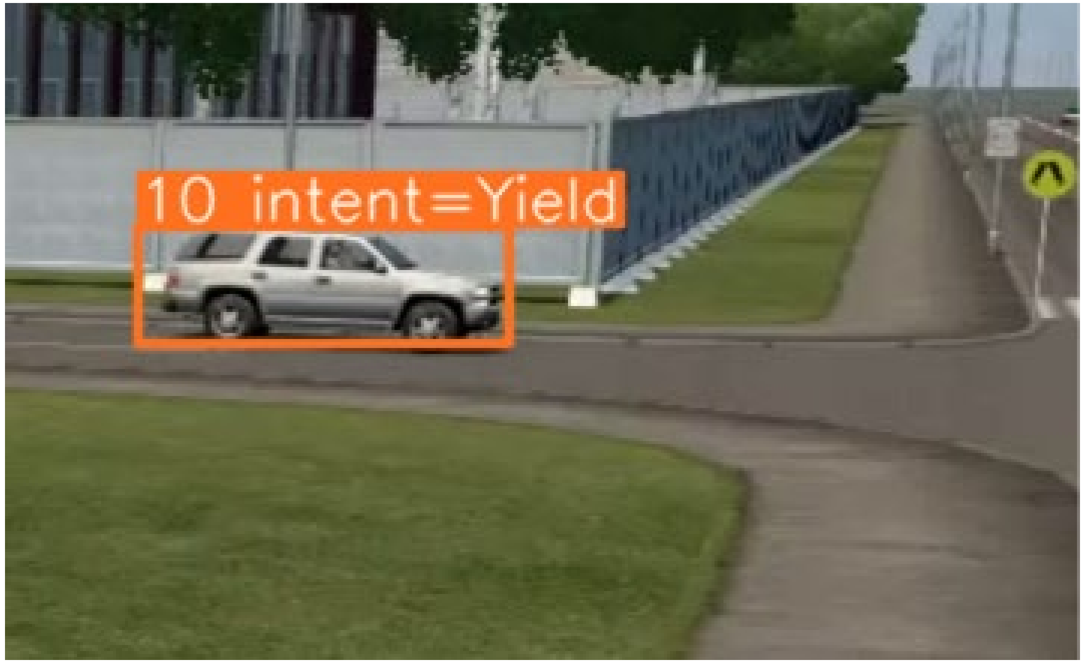
Results: DUKE
Intent predictions from the target vehicle at 30 m compared to observed action at the junction. Key : stop and yield = 1, merge yield = 2, slow no stop = 3, no slow no yield = 4

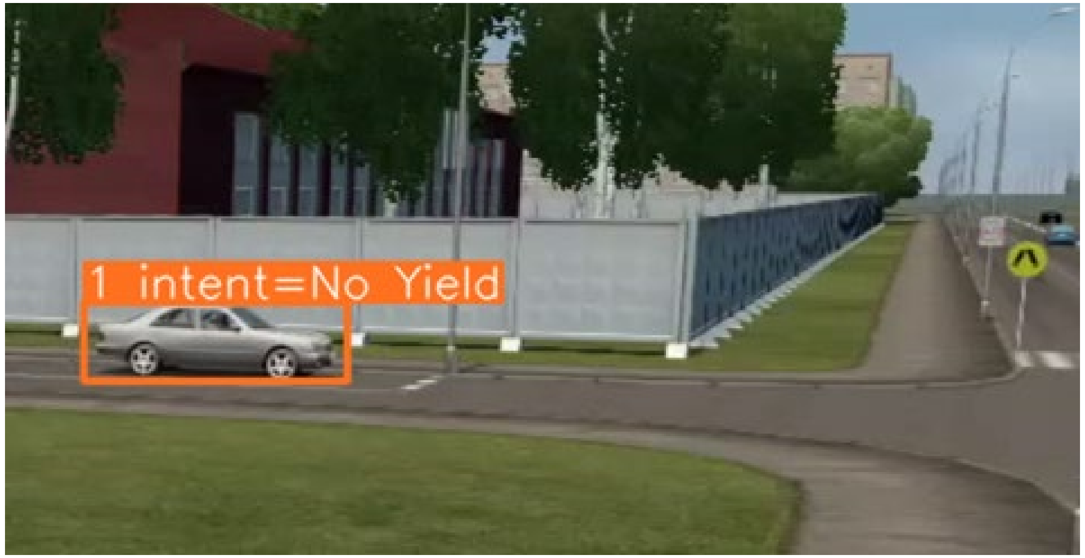
Intent prediction												
Predicted	1	1	1	2	2	2	3	3	3	4	4	4
Observed	1	1	3	2	1	1	3	3	4	3	4	4
Precision	1 = 66.7%, 2 = 33.3%, 3 = 66.7%, 4 = 66.7%											

Results Duke

Realtime data capture allowed us to make an intent prediction 30 m from the junction and update every 1 s until the stop line.

Top image image target vehicle predicted to yield, and the bottom image shows the target predicted no yield.





Building a dataset

Study Junction A245

Discussion

Evaluation of the results indicates that although the intent predictions from both methods showed promise on simulated data, it proved the feasibility of the framework rather than evidence of a conclusive study.

New feature vectors to include driver traits.
(Peter Chapman, Notts.)

Summary and Next steps

- Empirical experimentation of live data
- Intent prediction from combined framework-data feeding into the system, increasing samples and thus increasing performance and accuracy.

Our subsequent study will focus on determining the effect of an intent prediction on an imminent collision scenario on a moving platform.

We will be using real data collected from UK highways

Incorporate Daisy and Duke into a single framework.

References

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Thank you

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