Drivers' Manoeuvre Classification for Safe HRI





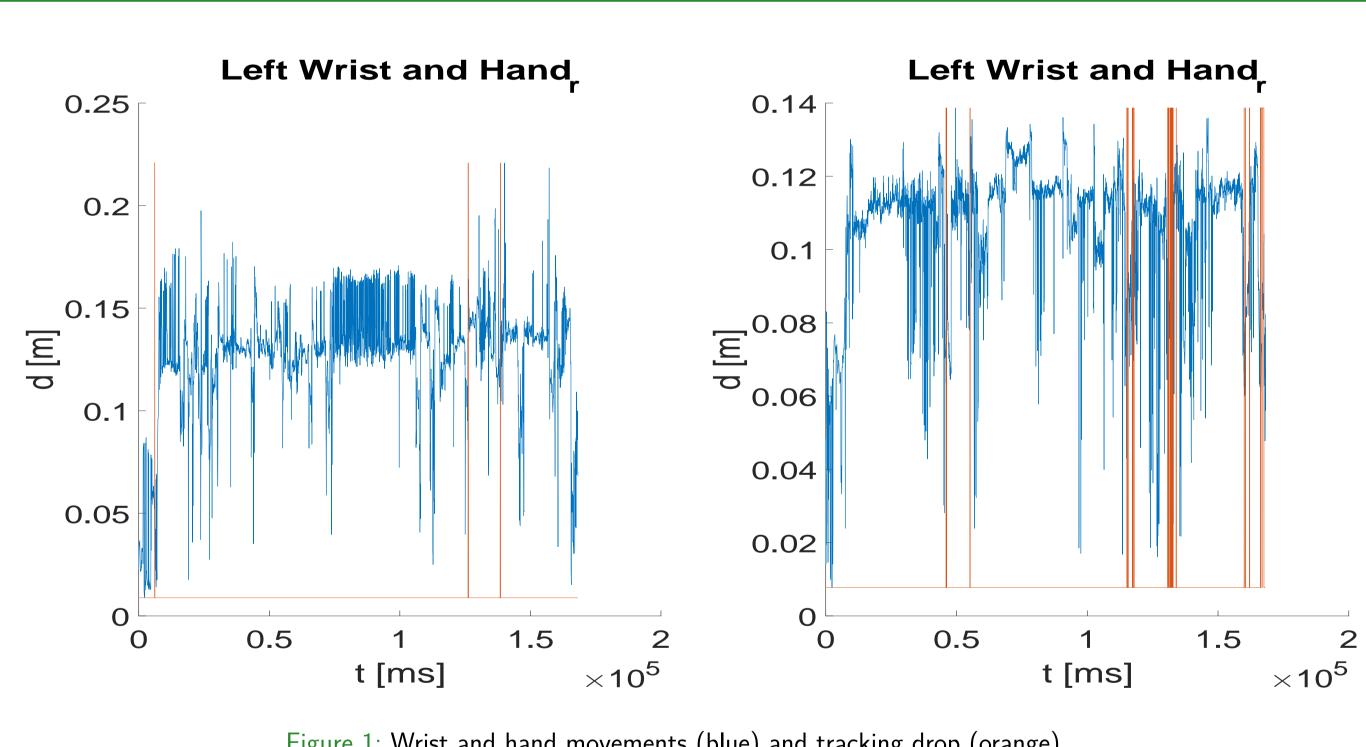
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Introduction

Human Robot Interaction needs to be safe. In dealing with powerful vehicles as autonomous cars, which are ever more like robots, ensuring safe interactions in both scenarios pose similar, yet daunting challenges[1]. For interaction with semi-autonomous cars, use of sensors to monitor the driver's behaviour could help to create new safety mechanisms. This work explores the concept of using motion tracking (i.e skeletal tracking) data to learn to classify drivers manoeuvres being performed.

Objectives

- ► To classify and later predict drivers behaviour, such that it can be used for control policies that ensure safety (e.g. compliance or enhanced ADAS).
- ► To examine reliability of classification using motion tracking in a driving scenario.



Methods

Figure 1: Wrist and hand movements (blue) and tracking drop (orange)

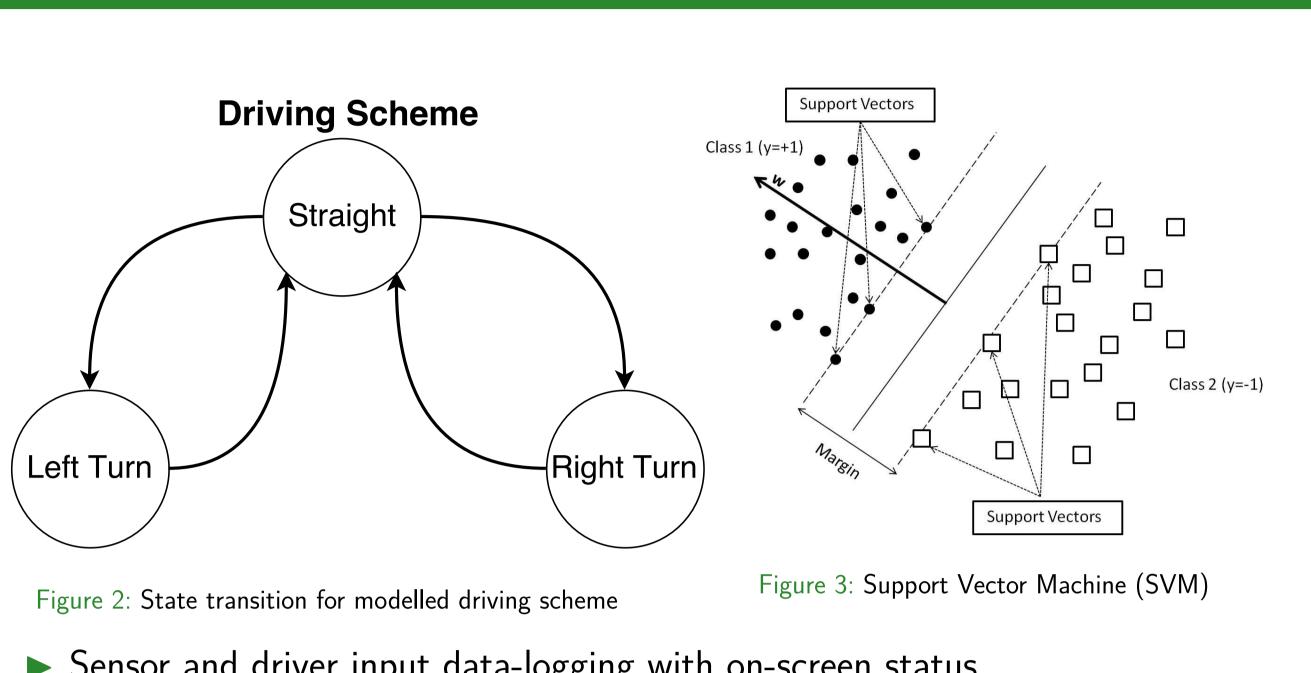
- ► High noise levels and occlusions make hand movements unpredictable, not suitable for data-driven methods and other limbs data erratic.
- Studies around muscle activation and movement patterns whilst driving [2] point towards the use of torso, shoulder and elbow data alone.
- Different pre-processing filtering techniques (i.e. Double Exponential Smoothing) Filter, hard whitening, soft whitening) were tried to further reduce noise.

Reference:	[1] K. Eder, C. Harper, and U. Leonards, "Toward on 09/07/2015).
	[2] Y. Liu, X. Ji, H. Ryouhei, M. Takahiro, and L.
	http://link.springer.com/article/10
	[3] YM. Huang and Sx. Du, "Weighted suppor



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Methods



- Sensor and driver input data-logging with on-screen status.
- ► Data-driven method modelling manoeuvre as a classification problem with kernel-based method (SVM)([3]).
- Reduced state transition model.
- ► Granularity of state defined in modelling process.

Results

The proposed method is able to learn to classify 3 manoeuvres using a relatively small dataset per test subject, exploiting the repeatability of arm movement whilst performing a driving manoeuvre, with mean precision above 85%, including the F1 metric which is above 90% in all cases; the F1 metric shows a balanced performance between missed classifications and true classifications, with low number of missed classifications whilst discriminating between manoeuvres.



Figure 4: Simulator and Kinect V2 Integration

Is the Safety of Human-in-the-Loop Robotics: Challenges and Opportunities for Safety Assurance of Robotic Co-Workers", arXiv: 1404.2229 [cs], no., Apr. 2014, arXiv: 1404.2229. [Online]. Available: http://arxiv.org/abs/1404.2229 (visited) Lou, "Function of shoulder muscles of driver in vehicle steering maneuver", en, Science China Technological Sciences, 55, no., pp. 3445–3454, Sep. 2012, ISSN: 1674-7321, 1869-1900. DOI: 10.1007/s11431-012-5045-9. [Online]. Available: .1007/s11431-012-5045-9 (visited on 09/28/2015). vector machine for classification with uneven training class sizes", in Proceedings of 2005 International Conference on Machine Learning and Cybernetics, 2005, vol. 7, 2005, 4365–4369 Vol. 7. DOI: 10.1109/ICMLC.2005.1527706.

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Conclusions

With a reliability of 80%, skeletal tracking data can be used to classify manoeuvres in a non critical simulation and opens the possibility for further improvements, other sensors integration and controller synthesis based on these predictions to ensure compliant performance.

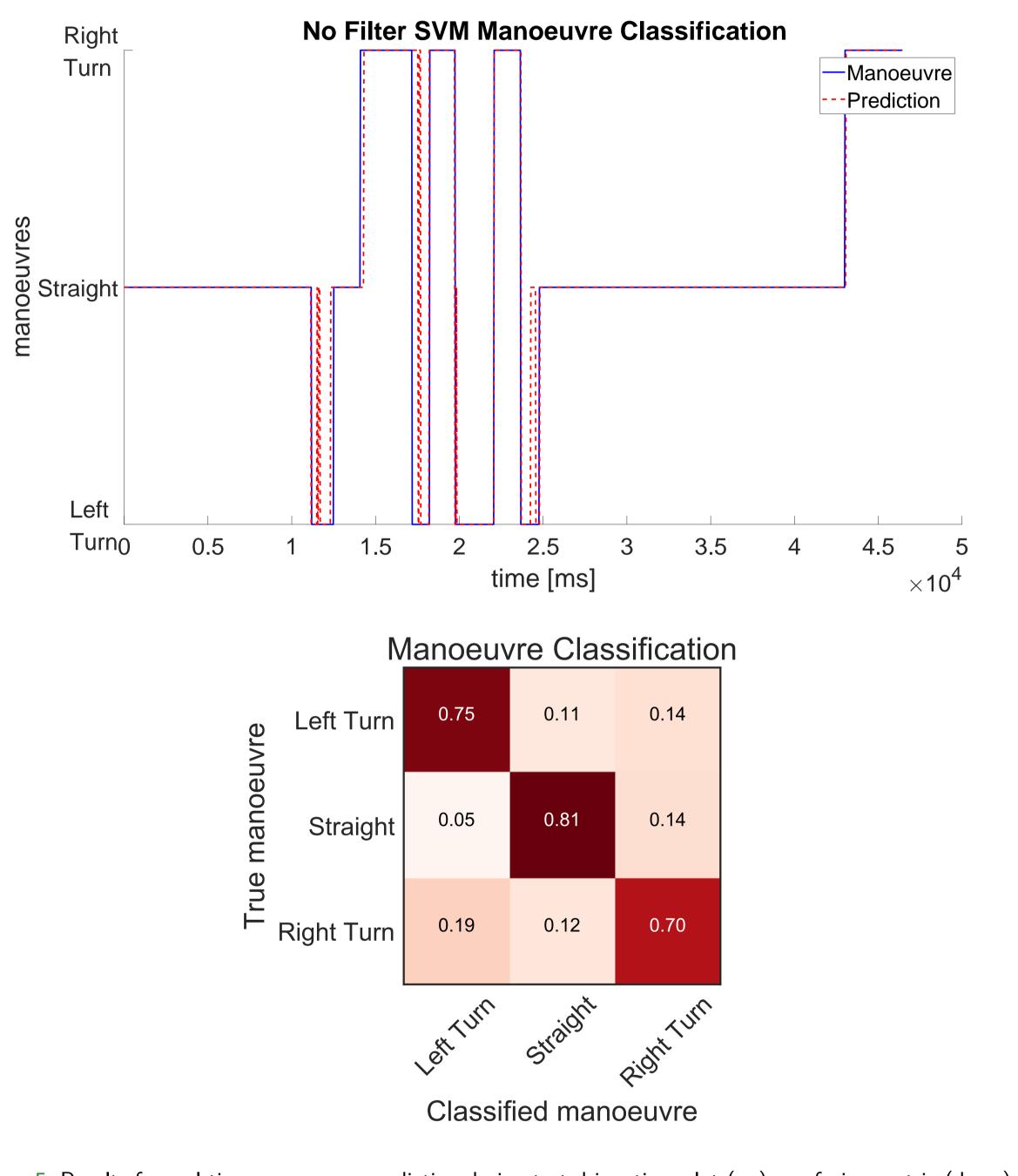


Figure 5: Results for real-time manoeuvre prediction during test drive, time-plot (up), confusion matrix (down)

Future Work

We will enhance our models by including eye gaze and heart rate measurements together with richer vehicle information (e.g. speed) and more complex driving scenarios that allow to simulate different mental workloads or distraction levels, in order to know how driver behaviour changes during manoeuvres when affected by different levels of distractions.

