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IMPLEMENTATION OF A VEHICLE DYNAMICS DATA ACQUISITION SYSTEM ON A SCALE PROTOTYPE TO DETECT DANGEROUS DRIVING PATTERNS

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Abstract. *A stronger demand for mobility causes increased risks to the lives of occupants inside vehicles, and pedestrians, so there is a need to monitor the dynamic parameters regarding driving behaviour that risks the integrity of the vehicle and its occupants. In this context, the aim of this paper is to demonstrate the modelling and implementation of a vehicle dynamics data acquisition system based on a scale vehicle prototype, whose design intent is the recognition of dangerous driving patterns. While currently available vehicle dynamics control systems involve the necessary sensing resources, there is still a need to recognize driving hazards and thus improve the ability to mitigate them. The article begins with reviewing the state-of-the-art in vehicle sensing technologies and driving behavior recognition, and proceeds with the methodology about selecting the scale vehicle platform, followed by the installation of the respective devices and the data processing technique. This enables the implementation of the vehicle dynamics data acquisition system on a scale vehicle prototype for collecting dynamic data. While monitoring requirements were captured based on the recognition of current technologies, the team kept in mind the implementation of a vehicle system at scale. The data acquisition system consists of in-vehicle ordinary sensors, capable of collecting dynamic data. Data collection on the dynamic behaviour of the vehicle is done successfully, with prospects to improve data accuracy at scale and route implementation in real vehicles. There is, however, in future works, the need of establish dynamic patterns representing dangerous driving circumstances, and required processing systems dedicated to the recognition and communication of such data, internally and externally to the vehicle.*

Keywords:
Vehicle dynamics, Data acquisition, Dangerous driving, Pattern analysis.

1. INTRODUCTION

The World Health Organization (2018) points out speed and distractions as major factors in traffic incidents with time and asset losses, frequently resulting in human fatalities. A significant component to causing this is the willingness of drivers to engage in dangerous driving which frequently involves a compromise between the vehicle speed against others in traffic and the ability to focus, predict and respond to emerging traffic circumstances. Bengler *et al.* (2014) report the historic engagement of the mobility industry with the aim of reducing the risk of failure in vehicle systems exposed to emerging traffic circumstances, the mobility industry develops driving assistance systems to reduce the costs of mobility, with effect to improving efficiency and safety.

In recent decades, significant advances in automotive technologies have revolutionized the market and industry. Tools such as the Anti-lock Braking System (ABS), Electronic Stability Program (ESP), and even the detection of unbuckled seat belts, were introduced in order to drive traffic to safer directions and reduce the number of traffic accidents, which in the year 2022 reached the mark of 64,447 records, 52,948 of them showing dead or injured (CNT - Confederação Nacional do Transporte, 2022). Despite this, the principles of dangerous driving still present themselves as a significant challenge to be faced by automotive safety in traffic, given their influence on the occurrence of accidents on the roads.

The objective of the present work is to develop, from the systems engineering approach, an event detection system, capable of using the sensors already present in a vehicle to identify the use cases determined based on the research. Recognizing dangerous driving patterns can lead to reducing the number of traffic accidents and recklessness effectively. Starting from a notification to the user, it is expected that the driver will be alerted of the harmful posture in question.

This article is organized in a literature review, addressing concepts related to systems engineering and dangerous driving, followed by the proposed methodology used by the approach for the development of the system. Finally, the results of the project will be presented and discussed, culminating in an initial prototype for testing.

2. LITERATURE REVIEW

Traffic accidents mainly derive from four factors (Treat *et al.*, 1979): human, vehicular, roads, and environment. As for the human factor, characterized by the concept of dangerous driving, the causes of traffic accidents include: speeding, driving under the influence of alcohol and/or drugs, cell phone use while driving, not using the arrows that indicate the intentions of manoeuvres, do not keeping distance from the vehicle in front. Therefore, an automated mechanism to detect and mitigate dangerous driving can collaborate to reduce traffic accidents.

However, the definition of dangerous driving also needs to take into account the specificity of each culture, differences in road infrastructure, and traffic codes in each country. In fact, drivers drive differently, for cultural reasons linked to the tolerance of risk from breaching traffic rules (Lindgren *et al.*, 2008), or to personality characteristics that could be linked to individual conduct in traffic (Mckenna *et al.*, 1998). These differences should impact not only the automated procedures to detect dangerous driving but also in prominent technologies designed to reduce the driver load, making the driving experience better and safer.

2.1 Data processing technique

One commonly used technique in processing vehicle dynamics data is the application of digital signal processing algorithms to improve the quality of the data. With regard to dynamic problems, transforms become quite effective into providing a transverse domain view about a dynamic parameter initially expressed in the time domain. This characteristic comes as a result of their effect of reducing the processing time for engineering calculations (Rao and Ahmed, 1976).

Among several methods available for that purpose, transforms have been used so far as useful tools to extracting relevant dimensions of the problem that seem too intricate to describe with time variables (Diniz *et al.*, 2010). While Fourier transforms are aimed at domain transposition - like from time to frequency - their representativeness is limited with working with transient data because they consider a single amplitude in the time domain. For transient situations, wavelet transforms can be used to decompose the data into different frequency components with varying amplitude, enabling the identification and filtering out of transient disturbances and noise (Chan, 1994).

A wavelet family is built from a function called “mother wavelet” or “base”. The “child wavelets” are then formed by the translation and contraction of the “mother wavelet”. If a defines the scale and b the translation, a base or “mother” wavelet can be written as shown in Eq. 1.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \tag{1}$$

This equation represents the wavelet function $\Psi_{a,b}(t)$ which is built from a "mother wavelet" or "base" function Ψ. The function $\Psi_{a,b}(t)$ is a scaled (a) and translated (b) version of the mother wavelet. The scaling factor a determines the frequency of the wavelet, and the translation factor b determines its position in time. The factor $\frac{1}{\sqrt{a}}$ ensures the energy of the wavelet remains constant across different scales.

2.2 Data-supported detection of dangerous driving

Research aimed at developing mechanisms to detect dangerous driving has been growing in recent years. The available techniques differ by consuming different data to detect the driver's attention through eye movements, mouth, ECG, and also car movement data Kaplan *et al.* (2015). Typically, the use of vehicle data allows some form of driver anonymization, while imagine processing require filters to drive anonymization. The analysis of the vehicle speed, which is a feature easily captured through sensors embedded in the vehicle itself and even in smartphones, is one of the commonly investigated alternatives to detect dangerous driving behavior.

Again, through these data, Eboli *et al.* (2017) classified drivers using thresholds to identify three types of driving behaviours: safe, unsafe, and safe but potentially dangerous. Dataset was obtained using 27 drivers driving in a rural road in Italy. Only four drivers were classified as safe behaviour. The major part of drivers were classified as unsafe and potentially dangerous, even if they developed low speeds, which actually can disturb the expected traffic.

Johnson and Trivedi (2011) applied Dynamic Time Warping (DTW) to classify drivers in non-aggressive and aggressive using as input data accelerometer measurements, gyroscope, magnetometer, GPS, and videos. Evaluation was conduced using a modest dataset.

Another well-researched alternative is the support of Machine Learning (ML) to categorize drivers. In Lattanzi and Freschi (2021), two different classifiers (Support Vector Machine (SVM) and feed-forward neural network) were used to recognizing safe and unsafe driving behaviors using in-vehicle sensor data. To avoid the need of great amount of data, supervised learning approach based on labeled data points can be applied (Wang *et al.*, 2017).

2.3 Machine learning algorithms on dangerous driving

In Khodairy and Abosamra (2021), the main research contribution is a slightly more detailed behavioral classification, in order to meet different contexts, such as driver protection, automotive insurance industry needs and ADAS requirements. Two classification models were used: three-class (normal, drowsy, and aggressive behaviors) and binary using as input data inertial vehicle measurement, GPS, and cameras. Therefore, a deep learning-based solution was applied. In Xiang *et al.* (2021), the proposed classification approach provided by a neural network was improved with the passenger's feeling scores about the driver.

Convolutional Neural Networks (CNN) have been widely applied to classify driver behavior using vehicle data (such as acceleration, gravity, RPM, speed, and throttle (the amount of accelerator pedal is pushed)) (Shahverdy *et al.*, 2020), and/or images obtained obtained through in-vehicle cameras (Zhang *et al.*, 2020; Masood *et al.*, 2020; Baheti *et al.*, 2018). In addition to distinguishing themselves by the type of data consumed, available technologies to dangerous driving detection also differ by the number of classes operated by the classifier. In Shahverdy *et al.* (2020), the CNN classifier is able to distinguish driver behaviour into five classes: safe or normal, aggressive, distracted, drowsy, and drunk driving, while Baheti *et al.* (2018); Masood *et al.* (2020); Zhang *et al.* (2020) divided driver behaviour in a much larger number of classes.

Controversially, Van Ly *et al.* (2013) found that features associated with acceleration events did not play a significant role in drivers classification. Braking and turning events showed more significant potential in drivers classification. Evans and Wasielewski (1983) investigated the influence of headways (time interval between successive vehicles' head) in high flow freeways with regard to the accident risk. Shorter headways corresponding to higher risk of accidents, and were found for drivers with prior accidents or violations, young drivers, male drivers, drivers with no passengers and as well as drivers not wearing seat belt. With regard to the vehicles characteristics, shorter headway was associated with newer vehicles and vehicles of intermediate mass.

3. METHODOLOGY

This section provides a comprehensive overview of the processes and methods previously discussed. It begins with the specification of the vehicle platform and subsequently delves into detailing the sensor payload and the assembly of the data acquisition system. The progression of tasks includes the processing and organization of relevant data in alignment with the experiment's design and driving scenarios, culminating in post-processing the data and presenting the results.

Furthermore, the paper proceeds to elucidate the implementation of the data acquisition system for dynamic experiments, encompassing the following key components: the vehicle platform, the sensor payload, track and driving scenarios, dataset extraction, and post-processing.

3.1 Vehicle platform

The problem of recognizing dangerous driving patters has inherent risk components in real-life scenarios: firstly, it is the risk to the integrity of experimental devices, which might involve injuries to the people involved; secondly, it is the risk to the integrity of infrastructure and buildings around the experiment, which might involve injuries to people that might roam around the area. These elements make it unfeasible to test dangerous driving in real-life scenarios. These risk factors demand the availability of both test vehicles and large-scale segregated testing areas, which are not available to the research team at the moment of experimenting.

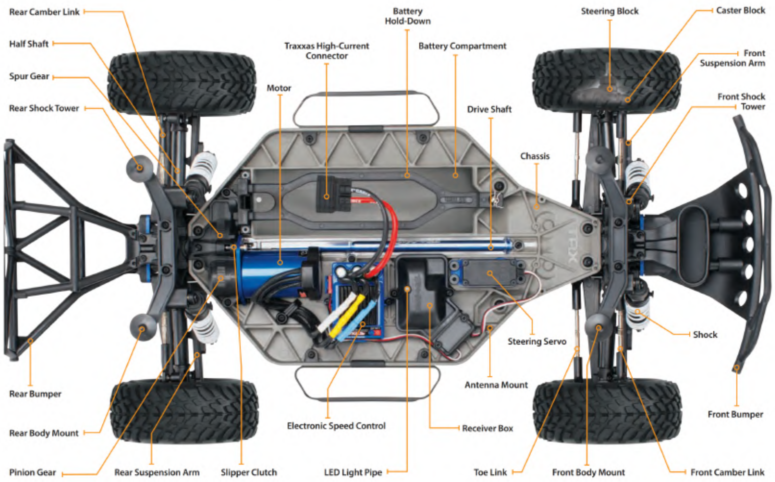

Figure 1: Example scale vehicle platform from remote-controlled vehicle model (Traxxas, 2023).

In facing the risk and costs of full-size experimentation, a scale vehicle platform as depicted in Fig. 1 proved to be affordable as a resource for acquiring dynamic driving data, as it could meet some requirements: (1) constructive and underpinnings similarity between scale model and actual cars; (2) ability to ride over imperfect surfaces even when intended for on-road testing; (3) property of reaching limit states of ground-tire interface and riding stability; (4) ability to carry a sensory and data processing payload for acquiring dynamics data; and, (5) portability and flexibility.

With priority to the dynamic similarity to actual vehicles, sensory payload capacity and the ability to reach limit state dynamics, the type of scale vehicle offering the best combination of properties for the experiment consists of the short-course truck as represented in Fig. 1. It tops the first criterion for the maneuverability of its 4-wheel independent suspension and powertrain on a 1:10 scale; each axle module includes a full-working differential, mated to u-jointed half driveshafts, and mounted along a 4-link suspension.

3.2 Implementation of sensory payload

The scale vehicle platform is intended to carry inertial and ranging sensors for the purpose of acquiring data about the dynamic driving parameters from the experiments. For that purpose, the following devices fulfilled the sensory needs: inside the vehicle shell, an iPhone6s device (depicted Fig. 2 (a)) is attached with zip ties to the inside the original transverse supports under the cabin volume to capture inertial data; outside the vehicle shell, a GoPro 10 Black camera (depicted Fig. 2 (b)) is attached to the rear face of the shell to capture inertial and imaging data, attached by adhesive pad.

(a) iPhone6s/phyphox (b) GoPro camera

Figure 2: Assembly of the prototype for the remote-controlled vehicle used in the data acquisition process.

The measurement hardware capability is defined by the specifications presented in Table 1. The iPhone 6s device carries two inertial units, an InvenSense MPU-6500 alongside a Bosch BMA 280, which provide the sensing ability related to acceleration (A) and turning rate (G) (Clover, 2014; Bosch, 2019a; Invensense, 2020); the GoPro camera has a 5.3K-maximum resolution imaging sensor, which is also capable of capturing video at 2.7K resolution with maximum frame rate at 240 Hz (Kirschenbaum, 2021). At the same time, it carries a Bosch BMI 260 inertial unit (Bosch, 2019b) alongside the image sensor, which provides the acceleration (A) and turning rate (G) data onto the video mp4-file metadata.

Table 1: Specifications of inertial units, iPhone 6s and GoPro 10 (Clover, 2014; Kirschenbaum, 2021)

Device		**iPhone 6s**		**GoPro 10**	
Inertial unit		**Bosch**	**Invensense**	**Bosch**	
Parameters		**BMA 280**	**MPU-6500**	**BMI 260**	**Unit**
ADC range		14	16	16	bit
Non-linearity		14	$\pm 0,5$	$\pm 0,4$	%
Ranges	(A)	±2 to ±16	±2 to ±16	±2 to ±16	g
	(G)	-/-	±250 to ±2000	±125 to ±2000	dps
Sensitivity	(A)	4096	16384	16384	LSB/g
	(G)	-/-	131	131	LSB/dps
Resolution	(A)	0,1	0,06	0,06	mg/LSB
	(G)	-/-	0,004	0,004	dps/LSB
BW Frequency	(A)	500	260	684	Hz
	(G)	-/-	250	751	Hz

Maximum sensitivity and resolution capacities measured at $\pm 2g$ acceleration range and $\pm 250dps$ turning rate range to enable comparison in similar specifications.

There is equal acceleration sensing capability between the devices regarding their acceleration ranges, which is the same for the high end of turning rate measurements. Nevertheless, the camera has a wider turning rate measurement bandwidth about the slow end, with link to its carrying an image stabilization processor. Another advantage by the camera is its higher bandwidth frequency, meaning its sensor is capable of a higher sampling rate than that of the smartphone.

In order to successfully detect dangerous driving through the use of inertial data, it is essential to complement the hardware capability with software that can make the data useful. For that purpose, the data acquisition system setup is depicted in Fig. 3.

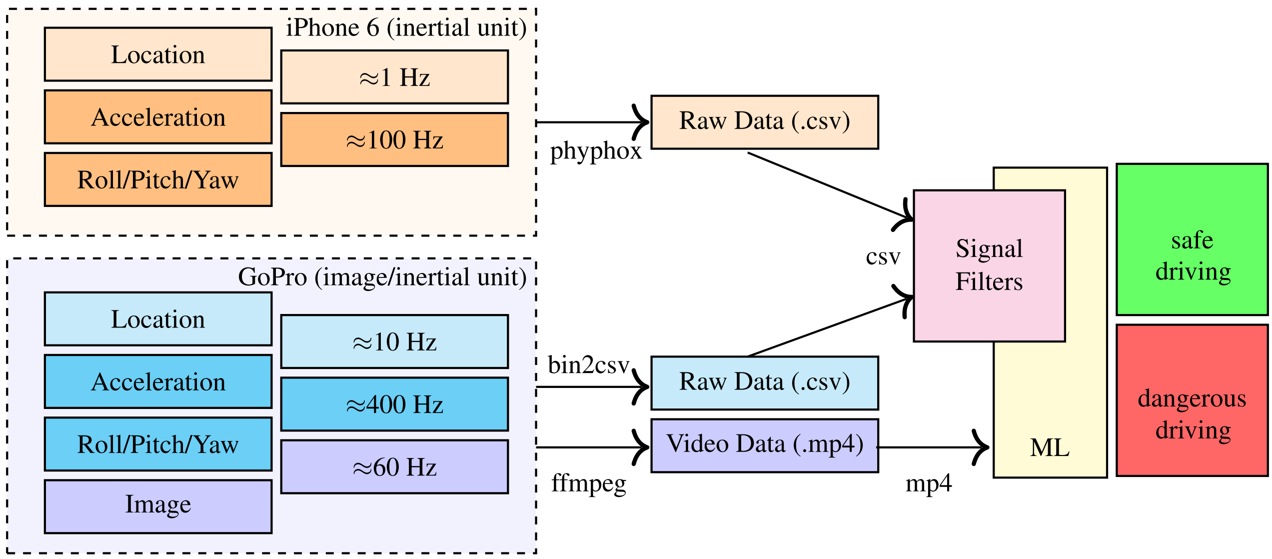

Figure 3: Data acquisition/filtering approach.

On the side of the iPhone 6s, we use the Phyphox application by Aachen University for sampling and exporting the inertial data, with direct export to csv-file (Phyphox.org, 2019) with acceleration, turning rate enabled at a sampling rate of 100 Hz, with location sampling at 1 Hz. By the camera side, The GoPro 10 captures images in several resolutions and frame rates, configured with a 4K image at 60 Hz frame rate for generating videos and their metadata. The mp4 video files from the camera were interpreted through a bin2csv converter tool applied to binary data from the ffmpeg codec for extracting the embedded inertial data at a sampling rate of 400 Hz, with location data sampled at 10 Hz (Irache, 2020).

Raw data from the system in Fig. 3 is post-processed to generate a set of features that are indicative of the driving behavior. The data collection process is iterative, involving initial data gathering, preliminary model training, and evaluation of the model's performance. Based on the model's performance, further data may be gathered to cover identified gaps or to improve performance in areas where the model currently underperforms.

3.3 Driving scenarios

The recognition of dangerous driving requires the experimentation about driving scenarios that include driving actions such as accelerating, braking, driving straight and cornering, with differentiating between safe scenarios with moderate driving and more complex and potentially dangerous maneuvers such as sharp turns, sudden braking, aggressive acceleration, and erratic lane changes. Varying road surface conditions can lead to changes in traction, leading to different degrees of tire slip and subsequently, changes in acceleration and angular velocity.

In the same manner, the track layout, whether it is straight or curved, and if the road has bumps and depressions, significantly impacts the forces experienced by the vehicle and hence the data captured by the onboard sensors. The experimentation with driving scenarios was carried out in a flat track with rough tarmac with a total length of ≈30 meters as represented in Fig. 4. Each driver started riding around 15 meters straight line to proceed performing curves over six poles spaced 3 meters from each other, and then running back to the starting line after the sixth pole.

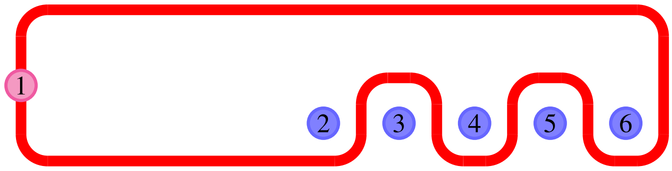

Figure 4: Schematic of the track on which driving scenarios were performed.

For the purpose of gathering data, eight (8) drivers using the remote-controlled vehicle platform performed laps following the track layout above with speeds up to 10 m/s. The driving sessions were organized in safe driving runs, and then in dangerous driving runs. Node 1 indicates the start/end of the route and each of the nodes 2-6 indicates a pole the driver should swerve around. The process of acquiring the dynamic driving data accounted for wet and dry tarmac conditions - there were two driving sessions - alongside the safe and dangerous driving scenarios, to improve the accuracy of the final dangerous driving model.

3.4 Dataset curation and post-processing

The available data includes outputs from the accelerometer and the gyroscope sensors in the devices, which provide basis for the recognition of dangerous driving patterns. However, this data is tampered with by external disturbances due to the vibration suffered by the system during the data acquisition. Therefore, a post-processing mechanism is imperative for the data used in the evaluation to be consistent. To deal with this drawbacks, we use wavelet functions (Strang and Wellesley, 1996).

Wavelet functions provide a comprehensive and adaptable approach to noise reduction. Unlike conventional Fourier transform techniques, wavelets can analyze non-stationary or transient signal behavior due to their capacity to vary in both frequency and duration. While the Fourier transform decomposes a signal into sinusoidal components of different frequencies, the wavelet transform uses wavelet functions that are localized in both time and frequency, so that transient features can be captured. Moreover, it provides a more detailed analysis of signals with time-varying characteristics.

Upon completion of the data acquisition process, the analysis transitions into the application of the Symlet wavelet, performed via a code implemented in MATLAB. Symlet, also known as Symmetric Wavelets, are a specific type of wavelet that belongs to the larger family of orthogonal wavelets. They are the family of wavelets chosen to process the data, as from satisfying the orthogonality condition and thus allowing for efficient signal reconstruction and analysis.

After importing the acquired data into vector variables, each newly generated vector undergoes processing via a one-dimensional wavelet. The resulting four vectors align with the three spatial dimensions (x, y, and z axes) and the temporal dimension (time). Notably, the wavelet transform allows comparing between the processed and original data by plotting both sets of graphics, with a comprehensive view of the data processing effects from signals and coefficient plots.

4. RESULTS AND DISCUSSION

The experiments were performed under open sky, dry tarmac, and overcast sky, wet tarmac. Eight different drivers were instructed to drive safely - applying care to maneuver the vehicle around the poles - and dangerously - trying to go as fast as possible through the poles. Both scenarios involved drivers colliding with the poles, yet the collisions through the dangerous driving runs had more energy, displacing and even tumbling the poles around. The driving runs took about 30 to 40 seconds regardless of the scenario, because there would be turns of missing the tangent point for each curve as drivers were going fast on the dangerous mode.

The system layout provides at least two major datasets per driving run, one from the smartphone and other from the camera. For the purpose of displaying the results obtained so far, we focus the data extracted from the phone, with a sampling rate of 100 Hz. The fundamentals to distinguish between safe and dangerous driving involve an assessment of the driving behaviour from sampling the filtered inertial data from a single driver performing both scenarios. The driving scenarios are depicted though their outputs: safe scenario in Fig. 5, and dangerous scenario in Fig. 6.

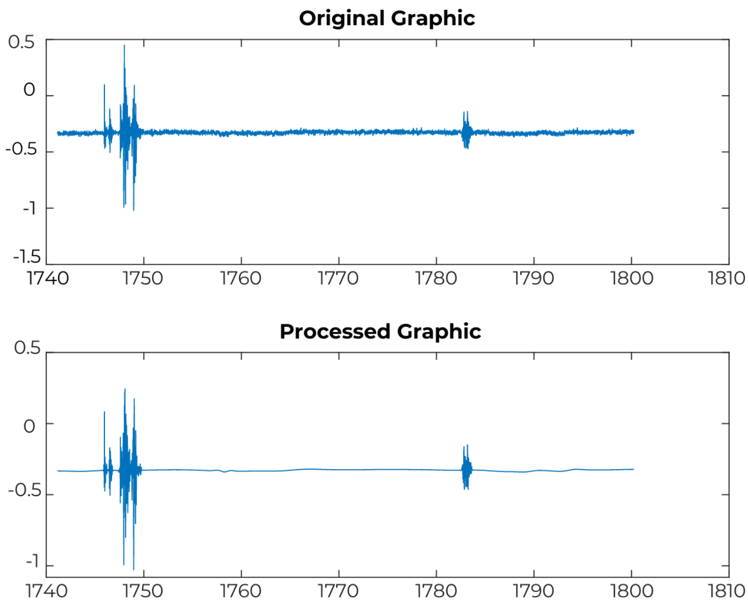

Figure 5: Accelerometer data in the x axis of safe driving scenario, dry tarmac.

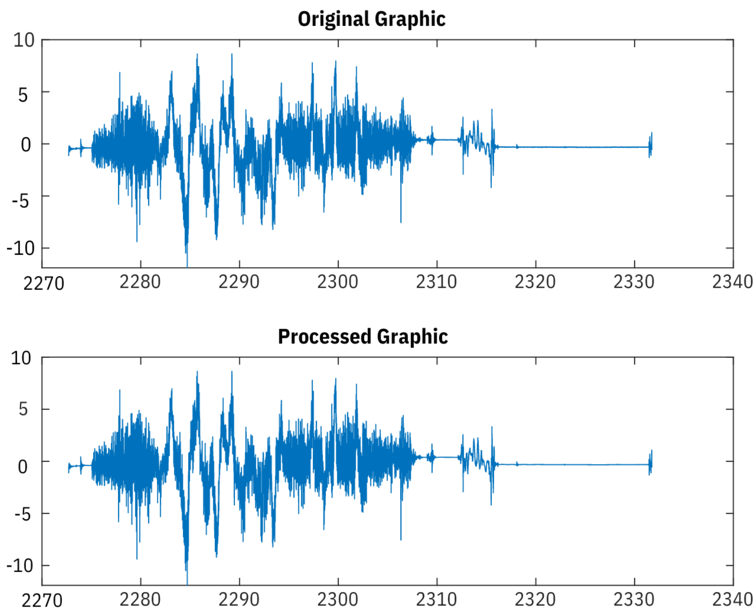

Figure 6: Accelerometer data in the x axis of dangerous driving scenario, dry tarmac.

Each figure displays the plot of a single driver run regarding its raw inertial data by the top and the resulting transformed data by the bottom. The measurements being plotted are the forward acceleration, pitch rate and yaw rate. Both plots - the raw and transformed inertial data - play through the same driving time. The effect from applying the symlet transform can be verified in terms of comparing the original and the processed signal plots, about the switches between negative and positive rates, their frequency through time, and their amplitude in processed regions.

The plots from both driving scenarios display the following features: there is effective low-amplitude denoising from the raw data plot to the processed data plot; the high-amplitude/high-frequency signals are maintained across the time period they appear as result from the dynamic system behavior. The tuning of the wavelet processor chosen does effectively enable the differentiation between progressive, low-amplitude signals resulting from safe and attentive driving in opposition to signals resulting from sudden and fast maneuvering

It's worth noticing that safe driving is characterized by near-constant acceleration ($\pm$ 0,05 m/s^2) outside of the first maneuver taking place around 1750 s, whereas dangerous driving shows a near-sinusoid pattern with amplitudes up to $\pm$ 7 m/s^2 with no noticeable denoising from the wavelet transform. The implication of this significant difference between the driving patterns in both cases regards the possibility of enabling algorithms including numeric and logic operations between raw sensor signals and processed signals over given time periods.

Moreover, the appliance of the wavelet transform is way more notable in the safe driving pattern, which shows that the external disturbances due to the vibration are way more explicit in safe driving than in dangerous driving.

5. CONCLUSION

Despite advancements in automotive technologies, dangerous driving behavior continues to contribute to accidents and fatalities on our roads. The persistent challenge of identifying these dangerous driving patterns has driven our approach in this article: the development of an event detection system using existing vehicle sensors. Our primary goal is to pinpoint the parameter values at which these hazardous driving patterns manifest, ultimately leading to their reduction.

Through the application of data-supported techniques, our research aims to effectively categorize unsafe driving behaviors. We have methodically utilized a scalable vehicle platform to ensure safer experimentation and dataset generation. Our objective is to pave the way for the creation of innovative solutions that promote safer driving practices and contribute to the reduction of traffic accidents.

In our forthcoming endeavors, it is imperative to establish dynamic patterns that accurately represent dangerous driving circumstances. Additionally, we will need to develop dedicated processing systems for the recognition and communication of such data, both within and external to the vehicle. This holistic approach will enable us to comprehensively address the issue of dangerous driving behavior and further enhance road safety.

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