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# From Human to Autonomous Driving: A Method to Identify and Draw Up the Driving Behaviour of Connected Autonomous Vehicles

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**Abstract:** The driving behaviour of Connected and Automated Vehicles (CAVs) may influence the final acceptance of this technology. Developing a driving style suitable for most people implies the evaluation of alternatives that must be validated. Intelligent Virtual Drivers (IVDs), whose behaviour is controlled by a program, can test different driving styles along a specific route. However, multiple combinations of IVD settings may lead to similar outcomes due to their high variability. The paper proposes a method to identify the IVD settings that can be used as a reference for a given route. The method is based on the cluster analysis of vehicular data produced by a group of IVDs with different settings driving along a virtual road scenario. Vehicular data are clustered to find IVDs representing a driving style to classify human drivers who previously drove on the same route with a driving simulator. The classification is based on the distances between the different vehicular signals calculated for the IVD and recorded for human drivers. The paper includes a case study showing the practical use of the method applied on an actual road circuit. The case study demonstrated that the proposed method allowed identifying three IVDs, among 29 simulated, which have been subsequently used as a reference to cluster 26 human driving styles. These representative IVDs, which ideally replicate the driving style of human drivers, can be used to support the development of CAVs control logic that better fits human expectations. A closing discussion about the flexibility of the method in terms of the different natures of data collection, allowed for depicting future applications and perspectives.

**Keywords:** automotive engineering; autonomous driving; driving behaviour; driving simulator; intelligent agents; pattern clustering

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## 1. Introduction

Automation is one of the essential features of the future industry, with concepts such as 5G, machine learning, and industry 4.0, becoming more realistic. The potential of autonomous systems has been proved in different fields, such as service robots [1], rescue [2], surveillance [3], construction [4], agriculture [5], education [6], transportation [7], hospitality and tourism [8], etc. However, the automotive industry is undoubtedly the crucial sector leading this new trend towards automation, by conducting intensive research and using creative and cutting-edge solutions to implement autonomous and human-like features in their products.

On the one hand, the rising concerns about the environmental impact of cars and, on the other hand, the issues of traffic congestion in large cities, suggest that the number of circulating cars must be reduced. Optimistic forecasts indicate that using autonomous vehicles will reduce the number of cars by up to 15% of what they are today, and we will need just a quarter of the parking spaces [9]. Besides, platooning a fleet of autonomous vehicles can reduce fuel consumption by 20–30% [10]. In addition, the introduction of autonomous vehicles can have a significant impact in terms of road safety. In 2001 [11], a study showed that 99.2% of car crashes involve human error, and in 2021 [12], this data is still confirmed: "over 90 per cent of crashes, the critical reason for the crash is driver behaviour". To reduce the effect of that factor, drivers should be willing to delegate the control of the vehicle to an autonomous driver. However, if the drivers believe that they can drive better than a programmed vehicle, they may resist giving away control to the autopilot [13]. That is why trust in automation is such an essential factor in determining the feasibility of an autonomous vehicle [14]. There are various ways to gain the users' trust in automation, specifically in automated driving. One example can be reference [15], where the authors studied the effect of creating a graphical representation of the virtual agent looking similar to the human driver displayed on the vehicle dashboard; they concluded that the similarities in appearances increase the users' trust. A factor that affects passengers' trust and comfort is the driving style of the autonomous driver [16]; therefore, knowing how to set the driving style of automated vehicles is needed to provide a better user experience.

These issues, coupled with the attempt to make safer cars and reduce the number of crashes, are leading us to a transition to Connected and Automated Vehicles (CAVs) [17–19]. CAVs might reduce the number of needed cars and, through a controlled and more efficient driving style, can also reduce pollution and congestion [20]. Furthermore, equipped with crash avoidance capabilities, autonomous vehicles are much safer and immune to human errors.

A critical step toward autonomous driving concerns the knowledge of driver behaviour and how human drivers perceive the driving environment, interpret it, and then make decisions and take action. The study of driver behaviour has led to the defining of various mathematical driver models. These models are the core cognitive foundation of the Intelligent Virtual Drivers (IVDs) that can control a vehicle if implemented into intelligent virtual agents.

To make autonomous vehicles reliable, the implemented driver model must be tested and validated frequently to fit the human driver's expectations. It can take the necessary actions in critical situations. IVDs can be used to support the development of different driver models, but due to their multiple settings, simulation software could generate many alternatives [21–23].

This article is part of the helpful research to define the driver as mentioned in the above models. It proposes a method to identify those IVD settings that can be used as reference driving behaviours for a given route. The driving behaviour of IVDs with different settings is compared with that of the real drivers to find out which IVD configurations better fit the driving style of the real drivers, on average or individually. These representative IVDs, which ideally replicate the driving style of human drivers, can be used to support the development of the CAVs control logic that better fits human expectations.

In Section 2, the paper provides a general background and an overview of IVDs and their applications, autonomous driving, and driving simulators. Then, Section 3 describes the developed method by highlighting its main steps. Section 4 proposes a case study set explicitly for the validation of the method. Section 5 describes the statistical analysis and clustering performed on the case study data and provides a detailed presentation of the results. Section 6 discusses the results of the data analysis and the effect of the virtual drivers' settings on their behaviour. Finally, Section 7 summarises the research and proposes the conclusions.

## 2. Background

Autonomous driving is an integration of various fields of science, and it is a multidisciplinary issue comprising several technologies and techniques such as intelligent virtual agents, computer vision, vehicle dynamics, artificial intelligence, and virtual reality. The term 'agent' is used in many disciplines, but there has yet to be a consensus on a definition accepted universally [24]. A simplistic explanation for an agent is a hardware or software-based computer system that: (a) can independently operate without the interference of a human operator; (b) can interact and communicate with other agents; (c) can perceive its environment and can respond to it; and (d) in addition to responding to their environment, agents can plan to follow a defined objective.

Researchers often tend to go further and allocate human-like characteristics to agents, such as mentality [25] or emotions [26], in addition to the definition. The process of decomposing agents into separate modules and coordinating the interactions between these modules is called agent architecture [27].

In [24], the authors propose the deliberative agent architecture, which contains a symbolic representation of the world. The agent in this world makes decisions based on logical reasoning. This architecture has led to the development of methods to implement the vision, speech, and learning capabilities in agents and create automated reasoning and planning processes. Implementing the mathematical driver models in the architecture of an intelligent virtual agent will consequently result in an autonomous driving agent. In this notion, autonomous driving is one of the agent technology applications.

To realise a fully autonomous vehicle, developing a reliable driver model, which can carry out the manoeuvres required in any possible driving scenario, is necessary. These efforts have led to the development of various driver models. The virtual driver, for instance, can be implemented with the 'Desired Path' model, as described in [28]. In this model, the driver is steering so that its trajectory will coincide with a sight point at a preview distance $L$ ahead of the current vehicle position. In this model, the driver tries to diminish the lateral deviation $\Delta yp$ from the desired path (Figure 1). The yaw rate error is defined as the yaw rate, starting from the current vehicle position and heading will move the vehicle in a direction that will intersect with the desired path after a preview time $Tp$.

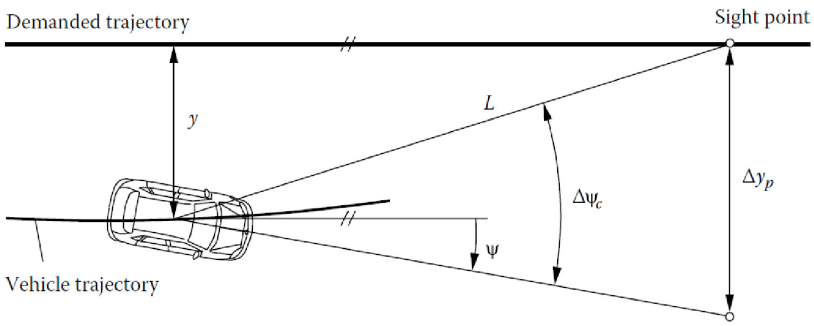



**Figure 1.** Desired path model [28].

Unfortunately, even if similar driver models are coherent with the developers' objectives, the resulting driving styles could be perceived in a very different way by the passengers of the CAVs [29]. The study of driving style for autonomous vehicles is essential as it directly affects passenger experience and comfort [30]. While some studies show that passengers prefer these vehicles to have a driving style similar to human drivers [31], other studies suggest the opposite [32]. In [32], the authors point out that some different driving styles of autonomous vehicles may not have a considerable difference in occupants' trust. Still, as the occupants gain more experience working with these machines, they tend to get more comfortable with them.

Driving style is the subject of many papers related to its definition and the way it is recognised [21]. As mentioned above, understanding human driver behaviour is crucial for developing realistic driver models to be adopted in autonomous vehicles. A specific driving style, such as aggressive or dynamic, is allocated to categorise drivers with similar behaviour. Identifying the driving styles of human drivers is also necessary to define energy management strategies [21] and tune the Advanced Driver Assistance Systems (ADAS). The characteristics of these systems are based on the average behaviour of a large group of drivers [33], but to provide more customisable designs, recognising the individual driving style is still necessary.

There are various definitions of driving style in the literature. In [34], the authors define the driving style as how the driver approaches the driving task and the vehicle operation. In [21], the authors propose a more inclusive definition of the way the driver operates the vehicle controls by also considering the condition in which the driving task is taking place, such as the weather or the state of the road; according to this definition, a driver can demonstrate different driving styles based on the external conditions. In [22], the authors define driving style as a "habitual", i.e., consistent on other occasions, a way of driving typical among a group of drivers, which can be either subconscious, i.e., automated over time, or deliberate and conscious.

In [35], the authors classify the driving style recognition process into two different categories, indirect (or model-based recognition) and direct (by analysing vehicular data). The model-based recognition method requires defining a driver model capable of describing the basic driving actions, such as lane changing, distance keeping, etc. Then, the driving style is recognised with the help of that proposed driver model. In [36], the authors applied a similar method to update the parameters of the dynamic driver model to match its control actions with those of the human operator involved in the same driving task. In the direct method, the driving behaviour is recognised by identifying patterns through direct analysis of vehicular data, such as speed, steering wheel angle, pedal positions, etc. Besides, in [35], the authors developed an algorithm to classify drivers promptly as 'aggressive' or 'moderate' based on the vehicle forward speed and the throttle opening. The sample group of drivers whose driving data were used to train that algorithm was previously labelled as aggressive or moderate based on a questionnaire they filled in before starting the driving task.

In the following, we define driving style as the set of all behaviours held by a driver (real or virtual) in road geometry, flow control, environment, and traffic conditions. The effect of a driving style can be revealed by vehicular features, such as speed, acceleration, steering, brake and gas pedal activity, trajectory, and energy consumption. Of course, a driving style must be parameterised according to vehicle characteristics and performance; also, as reference [37] points out, the road type and the traffic conditions must be recognised before assessing the driving style. From a modelling point of view, the driving style is defined by all models and related settings needed to realise the above behaviours.

Since a specific driving style is not directly connected to a particular driver model, developing a driver model is a process that needs extensive validation. To robustly represent a competent driver, the model should be tested in various situations that can happen in a natural driving environment. Driving simulators can play a crucial role in developing driver models. Since different driving scenarios can be simulated, the virtual driver can repeatedly test a road with a reduced cost and no risk of harm. In [38], the authors compared the behaviour of a group of real drivers in a test track and driving simulator with the behaviour of virtual drivers with two different driver models, the Desired Path Yaw Rate Error (DPYRE) model and the Modified Gordon and Magnuski model. They investigated the compatibility of each model with the behaviour of the real drivers and discovered that the DPYRE model generally represents a more realistic behaviour. In [39], the authors explored the impact of traffic complexity on the automation reliability expectations in terms of physiological responses in a driving simulator.

These studies use driving simulators to assess different autonomous driver models. However, it is still challenging to understand each model parameter's influence on the resultant driving style to make it as suitable as possible for others. The classification and recognition of driving style are usually obtained by using statistical and machine learning algorithms based on vehicular signals such as speed, acceleration, trajectory, and gas pedal use, as described in [40–42], but how to translate this data into an autonomous driver model is still an open issue.

The method described in this paper aims to support driver model development by comparing numerical and empirical simulation results to identify the IVD settings that can be used as a reference in driving behaviours for a given route.

## 3. The Proposed Method

The proposed method includes different steps, such as numerical simulation, an experimental test campaign with real drivers, and elaborating on the collected data. The purposes of this method are:

- discovering similarities within the IVD sample;
- creating clusters of IVDs;
- finding the IVDs that can be used as a reference for real drivers;
- categorising the real drivers into groups of drivers by distinguishing features.

Figure 2 shows the main steps constituting this method.

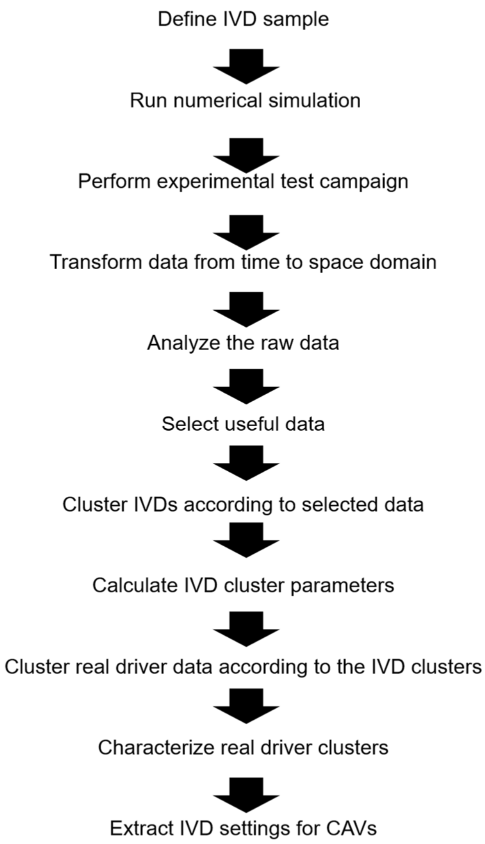



**Figure 2.** Workflow of the proposed method.

In the following, a description of the principles of the method is reported, while more details on calculations are proposed in Section 4.

### *3.1. Numerical Simulation*

This method starts by implementing the route to be analysed onto a driving simulation software and by setting all parameters used to perform the numerical simulation (e.g., car dynamics, environmental conditions, etc.). Different IVDs must be defined to collect behavioural data that can be used to characterise the driving style along the route. The behaviour of these different IVDs is set by modifying the parameters within the simulation software. The number of IVDs is set according to the parameters and their impact on vehicle control.

### *3.2. Experimental Test Campaign*

The experimental test campaign aims at collecting the same behavioural data with human drivers along the same route onto a driving simulator. These data are used to evaluate the IVD cluster representativeness compared with human driver behaviour; the

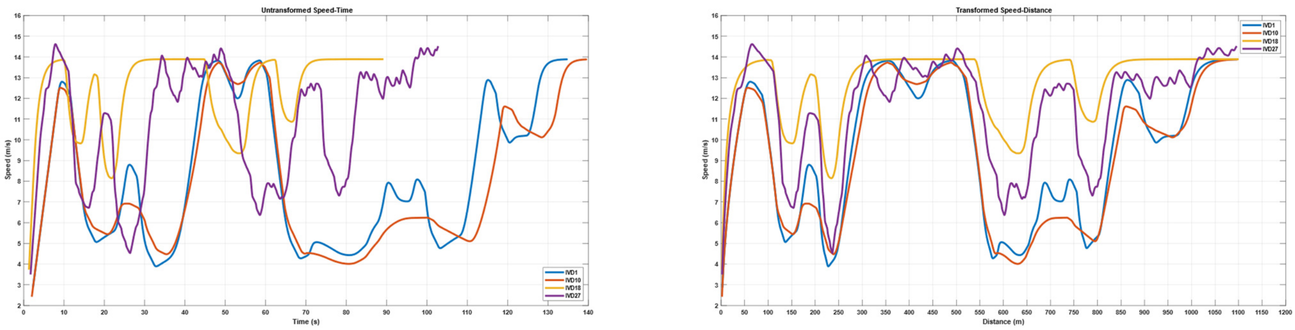
IVD clusters, including the highest number of human drivers, can be considered the most representative. It is worth noting that the proposed method is not grounded on a specific simulation software or simulator. However, to make the collected data comparable, the simulation software used for the IVD development should be the one used by the simulator.

### *3.3. Data Transformation*

Data collected during the simulation cannot be directly used for comparative analysis due to their different distribution in the time domain. The drivers' different behaviour in speed control results in different lap times; thus, the recorded data, in the time domain, for other drivers have different lengths. A function $g$ between Time and Distance must be defined to make the data suitable for comparison. This function has been elaborated with MATLAB (MATLAB R2021b, MathWorks, Inc., https://www.mathworks.com/products/matlab.html (accessed on 31 May 2022)) starting from the numerical data and then, by calculating the inverse of this function, the new value of time can be reproduced to fit a new track segment of regular points in space (1).

$$new\ Time = g^{-1}(Vehicle\ Distance) \quad (1)$$

Figure 3b illustrates the effect of transformation on the original speed signals Figure 3a. It is observed that the transformation makes it possible to compare different drivers also in specific segments of the track.




(**a**) (**b**)

**Figure 3.** (**a**) Untransformed speed signals having different lengths for different drivers, (**b**) the transformed ones.

### *3.4. Preliminary Data Analysis*

After the transformation, the trends of collected data must be analysed to remove possible outliers and to identify the data that cannot characterise different driving styles. According to the route, some of the collected quantities could have a trend between the drivers being too similar or too distant, making these quantities insignificant. Correlation analysis of the data leads to identifying these quantities that can be neglected in further elaborations. This helps in understanding the effect of each parameter on the IVD behaviour and gives the researchers insight into tuning the virtual driver models that can adequately mimic real drivers' behaviour.

### *3.5. Clustering of the IVD Data*

The method used to cluster IVDs is based on calculating the Euclidean distance between the collected data. The calculation of the distances is performed as follows (2):

$$A_{ij} = \sqrt{\sum_{k=n}^{m} \left(s_{i,k} - s_{j,k}\right)^2} \quad (2)$$

The matrix $A$ contains the distance between all drivers, $s$ is the signal, $i$ and $j$ are counters for the drivers, and $k$ is the counter for the elements inside the vector of each signal. Every signal has the same length because of the transformation previously carried out from time to distance space. When the distance matrix $A$ has been calculated for all considered signals (e.g., gas pedal, brake pedal, speed, steering wheel angle, route deviation, etc.), they are separately normalised and then summed together without weights. In this preliminary implementation of the method, we considered that all signals similarly contribute to the driving style definition. Different priorities can be applied to each signal, and distances can be weighted accordingly before the sum. This possibility can help make the resultant drive style more dependent on specific signals. The normalisation of matrix $A_S$ ($s$ is the considered signal) is calculated according to the following expression (3):

$$A_{s,norm} = \frac{A_s - A_{s,min}}{A_{s,max} - A_{s,min}} \tag{3}$$

After the distance matrix is computed, a matrix $Z$ containing the list of pairs of drivers, ordered on distance, is calculated. Then a tree containing hierarchical clusters of its rows is built by a couple of drivers. This output can be graphically represented by a dendrogram, which also identifies clusters.

### *3.6. Further Statistical Analyses*

The statistical analysis is performed for signals of the same type, e.g., speed signal, between each virtual driver and all the real ones. The descriptive statistical indicators include mean, median, standard deviation, variance, min, and max. To measure how similar the behaviour of two drivers is, the Pearson's correlation coefficient [43], $r_{xy}$, between signals $x$, and $y$, of the same type was adopted and calculated for all signals between the two groups of drivers.

The comparisons within each group of drivers and between them are made by calculating the correlation coefficients and then averaging them through Fisher's $Z$ transformation [44].

By finding similarities within IVDs, it is possible to determine which set of parameters leads to similar behaviours among the IVDs. After the clusters of IVDs have been identified, new IVDs can represent their average behaviour by averaging their factors. Consequently, the number of drivers to be compared is narrowed down too.

### *3.7. IVD Parameters for CAVs Control Logic*

Once the representative IVD clusters have been identified, the settings describing the clusters could be used to support the development of CAVs control logic. Parameters can be calculated by averaging the sets of IVDs constituting the cluster. Although this step depends on the software used for the IVDs implementation, it can be generalised since the development of CAVs control logic grounds on the analysis and replication of predefined driving behaviours [45–47]. In this way, the control algorithms can consider a limited number of behaviours according to the number of identified clusters.

## **4. Case Study**

To validate the developed method, 29 IVDs with different settings were implemented and tested in a virtual driving scenario by using the simulation software CarMaker (CarMaker 10.0, IPG Automotive GmbH, Karlsruhe, Germany, https://ipg-automotive.com, accessed on 7 December 2022), and the output data of speed, steering wheel, gas, and brake pedal positions, lateral route deviation, and travelled distance, were collected for each of them. The 26 human drivers carried out the same driving task on a driving simulator, running the same simulation software. The human driver sample is 62% males and 38% females, and their age ranges from 21 to 26 years (M = 23.31, SD = 1.17). They had a valid driving license: 45% had more than 5 years of driving experience, whereas 55% had 2–5 years of driving experience. In all, 35% drive every day, 17% three times a week, 24% once a week, and 17% two times a month, whereas 7% never drove during the last three months before the experiment.

The driving simulator includes a realistic driver seat, a force-feedback steering wheel, a surrounding audio system, and a visualisation system providing a 175-degree horizontal view with three 32-inch monitors with a resolution of 1920 × 1080 pixels. To become familiar with the simulator, participants drove for 3 min within an adaptation scenario to check visibility, gas pedal, brake pedal, and steering wheel reactions.

To define the correct number of IVDs, we performed several preliminary simulations to have an evident difference among them in driving behaviour, and 29 was a good compromise between comprehensiveness and feasibility. According to this number, we decided to consider a similar sample for real drivers. However, the sample size can be increased to make the study more representative.

The driving task defined in CarMaker was to drive one lap around a designed road. The testing scenario developed for the case study does not include traffic. The road was a replica of a one-way urban road, about 1 km long and 8 m wide, with seven rectilinear and seven curvilinear segments. Figure 4 shows the geometry of the road.


**Figure 4.** Aerial view of the road used for the case study.

A Tesla Model S was chosen as the test vehicle from the CarMaker library. This vehicle was selected because its dynamic model can be compatible with the behaviour of future CAVs. The behaviour of the IVD is defined through the different sets of parameters that the user can modify in the virtual driver module of CarMaker. A specific set of parameters must be assigned to each driver to obtain virtual drivers with other characteristics.

Through the virtual driver module, the control actions of a human driver along a predefined path and under specific conditions can be replicated. These actions include steering, braking, gas pedal position, gear shifting, and clutch operations.

However, the behaviour of IVDs along the road according to the software settings is not easily predictable due to the combinatory effect of the multiple parameters defining the mathematical model of IVDs. To help users to parameterise specific driver characteristics, CarMaker provides a range of pre-set combinations of these parameters that can be chosen by changing the value, from 0 to 1, of three factors, namely *Dynamics*, *Energy Efficiency*, and *Nervousness*.

The *Dynamics* factor defines the parameters that mainly affect the IVD behaviour. It involves the vehicle speed, curve handling, and switching pedals. The higher the value, the more the IVD goes to the stability limits of the car. In this proposed study, the target speed that the IVD will keep was set at 50 km/h, which is the speed limit of the road.

In contrast, the speed control along the road is managed by the other three parameters: maximum longitudinal acceleration; maximum longitudinal deceleration; and maximum lateral acceleration. The dependency between the lateral and the longitudinal acceleration and between the lateral and the longitudinal deceleration is managed by two functions whose exponents can be set according to a specific speed. The curve handling is governed by the corner cutting coefficient, allowing the IVD to move off the given driving lane. The values of the corner cutting coefficient range from *0*, the vehicle drives in the middle of the driving lane, to *1*, the driver uses the whole width of the driving lane to calculate its static desired course. Finally, the *Dynamics* factor manages the time required to move the foot from the throttle to the brake pedal (pedal switching).

The *Energy Efficiency* factor influences the vehicle energy consumption during the test. This factor affects the time of acceleration and deceleration sequences to maintain the cruising speed and cut the speed peaks, the exploitation of the drag torque braking, and the tolerance between the vehicle speed and desired cruising speed.

Finally, the *Nervousness* factor affects the amplitude and the frequency of the time function that controls the gas pedal. High values increase the reactivity of IVDs to changes in road geometry or traffic conditions. As with the *Dynamics* factor, it can deeply characterise the IVD's driving style and increase fuel consumption.

Each of these three factors can be varied between 0 and 1, and to define the different IVD; each factor has been assigned the three values of 0, 0.5, and 1, resulting in 27 virtual drivers. In addition, two settings predefined by CarMaker and named "Energy Efficient" and "Stressed" have also been tested with driver numbers 28 and 29, respectively. Table 1 summarises the relationship between the three setting factors of the corresponding parameter values. During the simulation, vehicle trajectory deviation from the road centreline (route deviation), steering wheel angle, gas and brake pedal position, vehicle speed, travelled distance, and elapsed time was recorded for each driver. Subsequently, all data have been elaborated as defined in the proposed method.

**Table 1.** Relation between the three factors of the corresponding parameter values.

| Parameter | Unit | 0 | 0.5 | 1.0 |
|---|---|---|---|---|
| | | | *Dynamics* | |
| Corner Cutting Coefficient | - | 0 | 0.5 | 1 |
| Pedal switching | s | 1.1 | 0.6 | 0.1 |
| Max. Long. Acceleration | $m/s^2$ | 1.5 | 2.8 | 4 |
| Max. Long. Deceleration | $m/s^2$ | −1.5 | −3.8 | −6.0 |
| Max. Lat. Acceleration | $m/s^2$ | 1.5 | 3.2 | 5.0 |
| Exponent of g-g Diagram | - | 0.5 | 1.0 | 1.5 |
| | | | *Energy Efficiency* | |
| Acceleration/Deceleration interval | s | 0.5 | 5.5 | 10.5 |
| Drag Torque Braking | - | 0 | 0.5 | 1 |
| Speed Tolerance | - | 0 | 3.0 | 6.0 |
| | | | *Nervousness* | |
| Gas pedal function Amplitude | - | 0 | 2.08 | 10.01 |
| Gas pedal function Frequency | - | 0 | 1.25 | 2.5 |

## 5. Results of Numerical Simulation and Experimental Test Campaign

As described in Section 3, data transformation allows the plotting of the recorded quantities for all drivers (both virtual and real). Figure 5 shows the trend for all 29 IVDs, whereas Figure 6 shows the trend for all 26 real drivers.

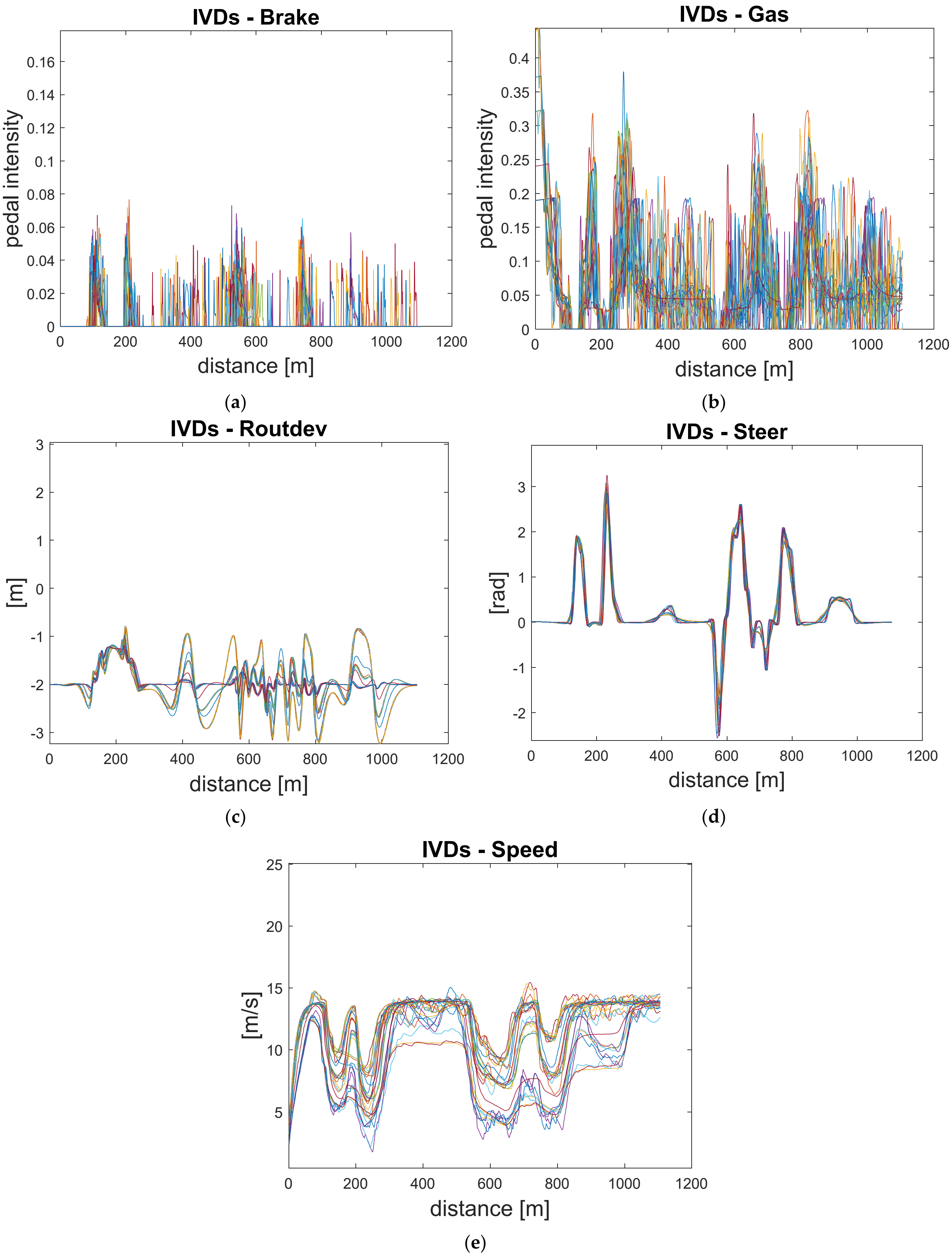



**Figure 5.** Collected data for IVD: (**a**) brake pedal intensity [0, 1], (**b**) gas pedal intensity [0, 1], (**c**) route deviation [m], (**d**) steering wheel angle [rad], (**e**) speed [m/s].

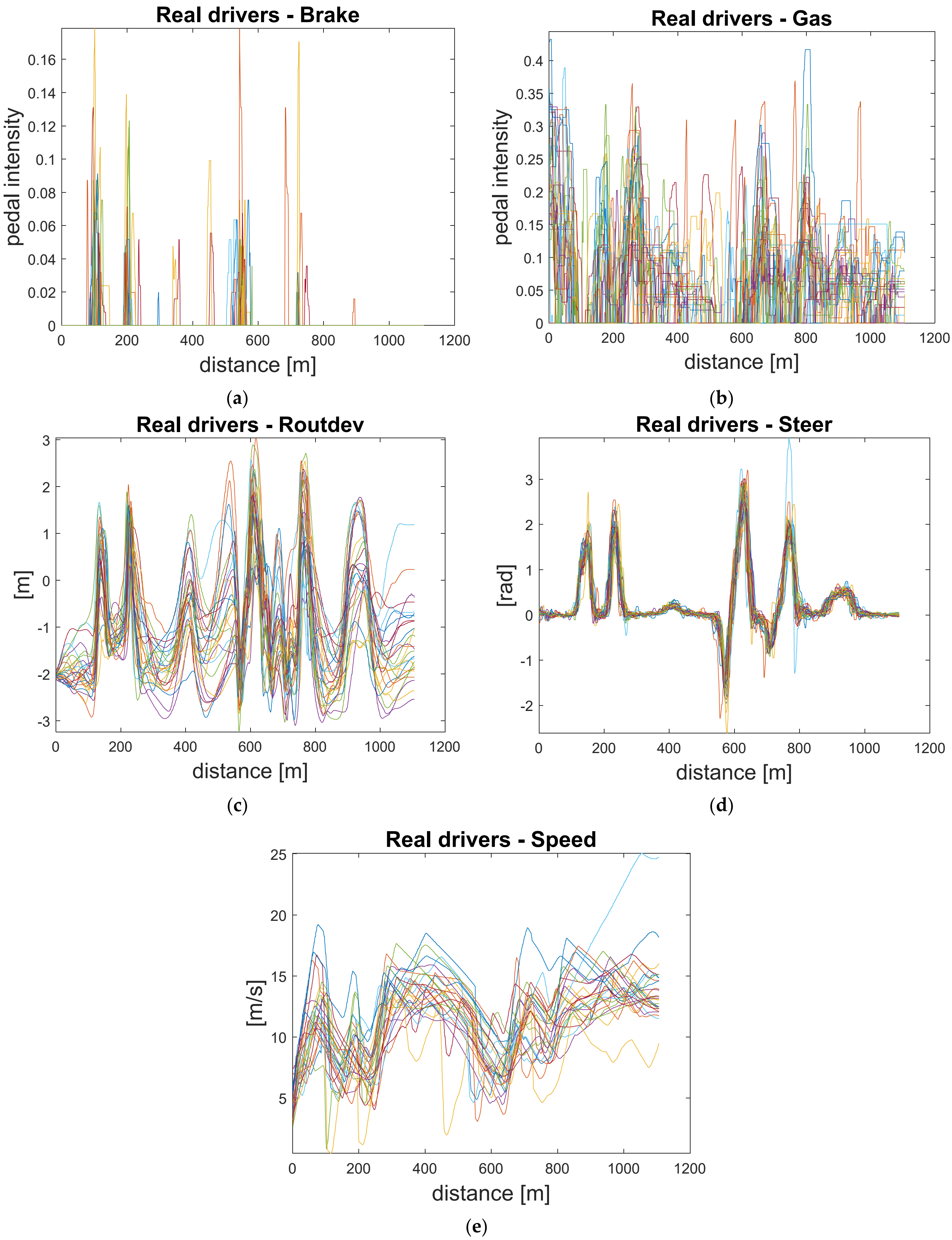



**Figure 6.** Collected data for real drivers: (**a**) brake pedal intensity [0, 1], (**b**) gas pedal intensity [0, 1], (**c**) route deviation [m], (**d**) steering wheel angle [rad], (**e**) speed [m/s].

These graphics show how the recorded quantities have different profiles. Some have a very similar trend (e.g., steering wheel angle), whereas others have a distribution with no mutual relationship (e.g., brake). Regardless, no patterns can be identified to define specific driving styles. A punctual comparative analysis within and between the two samples (IVDs and real drivers) does not provide any meaningful results. Consequently, these quantities will be clustered to discover similarities and differences between the real and virtual drivers and to find the virtual drivers that can be used as a reference for real drivers.

The correlation coefficients between the 29 virtual drivers show that the degree of similarity among the drivers varies based on the considered quantities. Whereas the drivers have highly correlated behaviour regarding speed and steering control, their behaviour in controlling the gas and brake pedals and the lateral vehicle position is not equally similar. A low standard deviation and a high mean correlation coefficient for speed and steering signals demonstrate that drivers have a more homogeneous approach to controlling these parameters.

Boxplots of Figures 7 and 8 present the correlation analysis within the IVD and real driver samples, respectively. Figure 7 shows the very high correlation value for steer and the relatively low value for brake signal. This fact is considered when deciding which quantities to use for clustering, as explained in the next section. Correlations for real drivers have almost the same trends, though it is worth noting that correlations are closer to zero for the brake pedal signal. This shows that the brake pedal usage for real drivers is less predictable than IVDs.

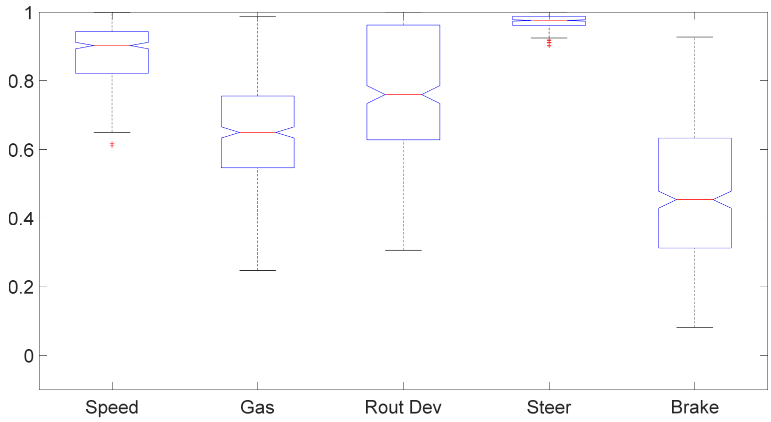



**Figure 7.** Boxplot of correlation coefficients between the 29 IVDs.

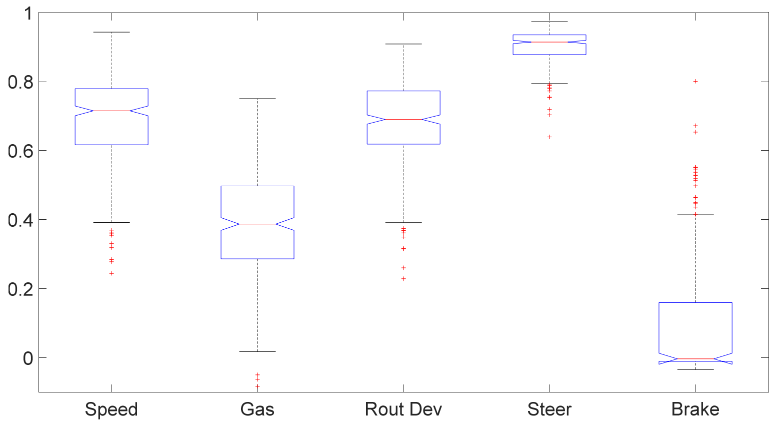



**Figure 8.** Boxplot of correlation coefficients between the 26 real drivers.

### 5.1. Clustering IVDs

The proposed method implies clustering the data to identify similarities within each group of drivers, as described in Section 3. Some of the collected data are not included in the clustering elaboration since they are insignificant in depicting a driving style. In particular, the brake signal exhibits an almost unpredictable behaviour concerning the exact points where it is different from zero (therefore, correlations of this signal are close to zero) and can be considered like noise. On the contrary, the steering wheel angle has a common trend for all drivers, the deviation from the average value is not significant, and its inclusion could make differences between drivers more difficult to emerge.

As discussed in Section 3, by finding similarities within each group of drivers, it is possible to divide them into groups of drivers with similar behaviour and treat each group as a single driver, representing the average behaviour of drivers belonging to that cluster. Distances are calculated using the three quantities, speed, route deviation, and gas. After calculating the distance vector of the drivers for each signal, these vectors were normalised and then summed together to get an overall distance vector.

It is worth noting that elaborating on each quantity alone leads to different clusters that cannot be compared. However, since the driving style is defined by a combinatory effect of other factors, considering these quantities together is the most appropriate way to treat these data.

Figure 9 shows the dendrogram of the distance matrix for the IVDs; the $y$-axis shows the sum of normalised distances of all the signals, and the $x$-axis shows the driver identification number. Three homogeneous clusters can be easily identified.

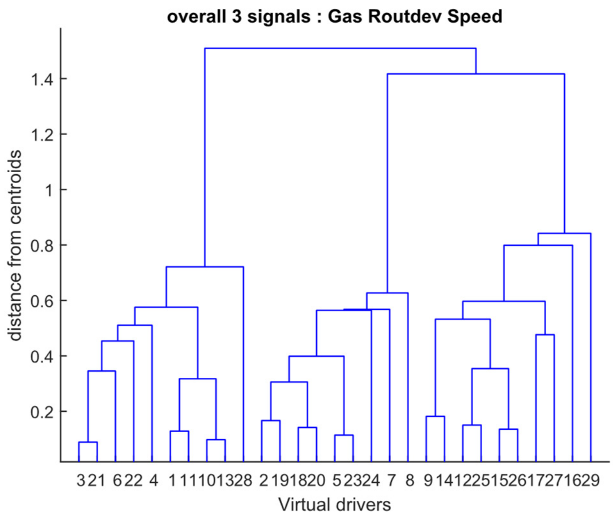



**Figure 9.** Dendrogram of IVDs clustered by gas, routdev and speed.

Then, three new IVDs can be defined in CarMaker to represent them by using the average values of the three factors, *Dynamics*, *Energy Efficiency*, and *Nervousness* of the drivers belonging to the same cluster. These three new IVDs represent the drivers inside each cluster (Table 2).

**Table 2.** Mean values and standard deviation (std) of IPG parameters by a cluster of virtual drivers.

| Cluster | | Dynamics | Energy | Nervousness |
|---|---|---|---|---|
| C1 | Mean | 0.0200 | 0.5500 | 0.4500 |
| | Std | 0.0632 | 0.4378 | 0.4378 |
| C2 | Mean | 1.0000 | 0.5000 | 0.5000 |
| | Std | 0.0000 | 0.4330 | 0.4330 |
| C3 | Mean | 0.5200 | 0.4500 | 0.5000 |
| | Std | 0.0632 | 0.4378 | 0.4082 |

It is observed that the three new virtual drivers have almost similar values of the *Energy Efficiency* and *Nervousness* factor, and it is the *Dynamics* factor that differentiates them from one another. Whereas the first cluster has a very low *Dynamics* factor, the second one has the maximum possible value of this factor, equal to 1, and the third cluster is between the previous two. It is worth noting that the *Dynamics* factor here is quite similar to the "Aggressive/Non-Aggressive" driving used by other authors [35].

Clusters for virtual drivers at thresholds equal to 0.9 (and up to about 1.3) are:

- C1: 1, 3, 4, 6, 10, 11, 13, 21, 22, 28;
- C2: 2, 5, 7, 8, 18, 19, 20, 23, 24;
- C3: 9, 12, 14, 15, 16, 17, 25, 26, 27, 29.

The correlation analysis between the three IVD clusters for all signals (Table 3) shows that the correlation coefficient between the second and the third IVD clusters is higher than the correlation between the first and second and the first and third pair. The higher similarity between the second and third IVD results from the value for their *Dynamics* factor. Whereas the first IVD has a minimal *Dynamics* factor, this value is moderate and high for the second and the third IVD, respectively, and the more evident similarity between the second and the third IVD shows the decisive role of the *Dynamics* factor in determining the driving performance.

**Table 3.** The correlation coefficients between the three IVD clusters.

| IVD Pair | Speed | Gas | Routdev | Steer | Brake |
|---|---|---|---|---|---|
| 1–2 | 0.782 | 0.546 | 0.359 | 0.965 | 0.220 |
| 1–3 | 0.909 | 0.702 | 0.681 | 0.976 | 0.372 |
| 2–3 | 0.942 | 0.786 | 0.768 | 0.990 | 0.755 |

### *5.2. Clustering of Real Drivers*

Figure 10 shows the dendrogram of real drivers obtained by applying the previously described method to IVDs. As seen from that figure, it is tough to single out a few homogenous clusters, which may be due to the random composition of the sample. In any case, this hinders the clustering of real drivers from their data.

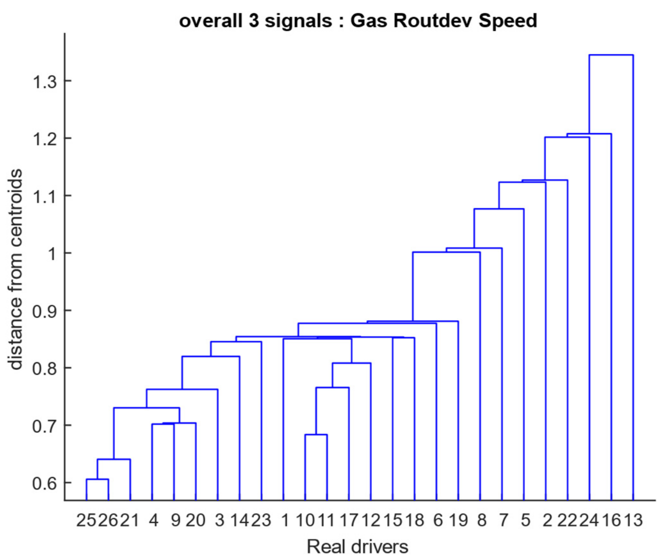



**Figure 10.** Dendrogram of real drivers clustered by gas, routdev and speed.

Then, another way was applied to cluster the real drivers. Distances between the real drivers and the three clusters of IVDs are calculated, and an overall distance matrix is generated. In the same way, in this matrix, for each real driver, there is a virtual driver cluster with the least overall distance, which consequently makes it the most similar virtual cluster.

The overall distance matrix shows that in 11 out of 26 cases, the second virtual cluster is the most similar virtual cluster, then the first cluster follows with eight, and the third one with seven (Table 4). In every case, to recognise the driving style of a real driver, the virtual driver with the least distance can be informative. Looking at the settings of the corresponding virtual driver in CarMaker can give a general idea of how *Dynamic* or *Nervous* the real driver is.

**Table 4.** Several real drivers are paired to IVD clusters and some of their features.

| Cluster | Number of Real Drivers | Females | Males | Average Age [Years] |
|---|---|---|---|---|
| C1 | 8 | 2 | 6 | 23.6 |
| C2 | 11 | 4 | 7 | 22.8 |
| C3 | 7 | 4 | 3 | 23.5 |

Distribution by gender of real driver clusters shows a moderate bias of females for cluster 3 and a higher frequency for clusters 1 and 2 for males. The average age per cluster is slightly lower for cluster 2.

The highest frequency of male drivers and the lowest average age of real drivers matching with the second IVD cluster can hint at the connection between the *Dynamic* factor and the driving style of real drivers. Of course, having a larger sample of real drivers could help notice this phenomenon significance. Still, younger drivers seem to have a more *Dynamic* driving style than the other real drivers.

### *5.3. Descriptive Analysis of Clusters of Real Drivers*

Descriptive statistical indicators will better show the similarities and differences within the real drivers' clusters, as shown in Table 5.

**Table 5.** Mean correlation coefficients within real drivers' clusters.

| Cluster | Speed | Gas | Routdev |
|---|---|---|---|
| C1 | 0.71 | 0.39 | 0.74 |
| C2 | 0.67 | 0.43 | 0.68 |
| C3 | 0.70 | 0.35 | 0.64 |

It is observed that in the case of speed and routdev signals, except for a few drivers, the real drivers have a homogeneous distance from one another. In contrast, the distances between drivers vary for the gas pedal position. A high mean correlation coefficient confirms this for the speed and routdev signal compared to the relatively lower mean correlation for the gas pedal signal. This suggests that the real drivers are more similar in controlling the vehicle speed and lateral position. The slightly higher interquartile range and standard deviation are also evidence of a higher variability between the real drivers in maintaining the position of the gas pedal.

### *5.4. Settings for CAVs*

The data elaboration reveals that the three clusters may also represent the sample of real drivers involved in the experimental campaign. According to the proposed method, the parameters of Table 2 can be used to define the three reference driving styles for developing a CAVs control logic that can comply with the human expectations for the road under investigation. It is essential to notice that the proposed method allowed identifying the IVD parameters that generate the driving styles that better fit with those of human drivers. In addition, having a validated IVD setting reduces the need for human drivers in repetitive simulation tests where only geometrical or controlling parameters should be investigated.

## 6. Discussion

IVDs with customisable behaviour provide a fast and efficient way to replicate the driving style of human drivers. Since it is difficult to determine the actual driving behaviour of participants using questionnaires, the researchers can reproduce an IVD with any desired behaviour to compare it with the human driver and consequently identify their driving style [35]. In a similar study [47], the authors tried to characterise the driving skill of the drivers by using pattern recognition methods; they manually labelled the participating drivers based on their hours of driving experience and used the coefficients of the Fourier transform of the steering wheel angle signal as a discriminating feature to train pattern recognition algorithms based on, e.g., support vector machines or artificial neural networks.

The three parameters defining the CarMaker setting for the driving model are an easy way to draw up a driving style. However, one must consider that each driving model parameter can be modified. This opens a broader range of combinations that are more challenging to deal with but can better fit real drivers' driving styles, especially when the routes to be simulated are complex. The main goal is achieving a "realistic" performance according to the optimisation of vehicular indices. They do not yet consider how a specific driving style affects driver or passenger emotions and how it is accepted. Driving style can solicit deep human body reactions [48], and this aspect should be included in future research by considering physiological, attentional, and psychological data, as discussed in [49].

It is worth underlining that, contrary to a virtual driver, a real driver may arbitrarily change his driving behaviour during the trial. This issue is possibly caused by fatigue, stress, or even the same drivers' characteristics and is more likely to happen on a long route. These behavioural changes are difficult to replicate, particularly in recognising the moment they are activated. In addition, the composition of clusters of real drivers shows a number slightly higher for cluster 2 (42%), followed by cluster 1 (30%), and cluster 3 (28%). They cannot be considered entirely homogenous, but no prevailing and adsorbing cluster exists. Understanding this behavioural aspect is, of course, an aim of future research.

Another consideration should be for the elaboration of the IVD clusters. They are calculated by summing distances from different signals without weighing them and then giving them the same importance. Future applications of this method can lead to identifying different possible weighting of vehicle signals, a collateral benefit that our proposed method can provide.

Though this method does not depend on the path and scenario used for the trial, the outcomes may be strongly dependent on them. The environmental scenario used for driving simulation affects the behaviour and emotions of real drivers [50], then affects driver behaviour and possibly the associated driving style. The IVD cannot perceive these features; therefore, each scenario must be analysed from different perspectives. Traffic conditions highly affect driving behaviour, and dedicated experiments must be conducted to retrieve further data to apply this method in different driving scenarios. However, we can assess that this method does not limit the number of variables to be considered and then makes possible the draw-up of a CAV driving model suitable for all specific driving scenarios.

In addition, using simulation software and a driving simulator implies building the road scenario that makes the application of this method more demanding compared with other approaches where the driving style is inferred from actual driving activities. The scheme in Figure 11 shows how the method can be interfaced with the main procedures found in the literature for drivers' driving style classification. Solid-line blocks identify the components of this method. In contrast, the dashed blocks represent different data collection methods and possible interactions with those to classify drivers' driving styles. Essentially, we have identified three ways to retrieve driver behaviour samples: driving simulation, on-field collection and questionnaires, and two ways to classify drivers' driving styles: correlation with the IVD reference samples and pattern recognition (such as by neural networks [51], k-means [35], machine learning techniques [52]). From the scheme, the hinge role of IVD samples is clear.

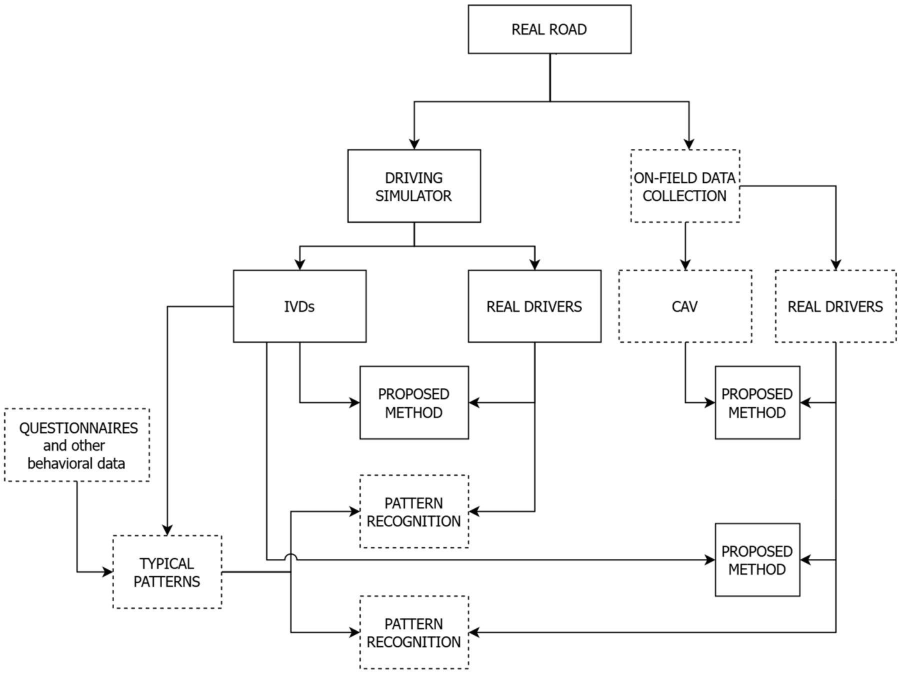



**Figure 11.** Scheme showing how the proposed method can be interfaced with different data sources for drivers' driving style classification.

This method can be further extended to data collected in a natural environment, provided that the route is identical to the simulated one. It is worth noting that this method can be generalised for data acquired in both simulated and natural environments. However, the sensors used in the actual context should provide signals that can be compared with those produced with the simulation of IVDs. One application limit could cover scenarios with a multipath choice where different routes can be determined according to drivers' preferences. However, if the number of different paths is small, the simulation of the IVD running can be separately performed for each route, reducing the problem to the initial one. The presence of stops during driving hinders the comparison between signals, but also, in this case, there is an expedient to apply the method again. It simply requires that all records referring to the stopped vehicle are cancelled, thus creating a continuous sequence of a running car.

The limits which should be faced in the future development of the research are:

- The presence of other circulating vehicles (creating non-deterministic interferences);
- random events (such as pedestrians or animals crossing the road);
- pedestrians walking on the sidewalk (causing distraction);
- visibility condition (e.g., for rain, fog, other weather conditions, or night-time);
- road pavement condition (for rain, snow, ice).

## 7. Conclusions

The current interest in CAVs leads researchers to develop driving models that mimic drivers' behaviour to improve passenger well-being. These aims can be achieved after analysing and classifying real driver profiles through the primary vehicle signals, such as speed, brake and gas pedals, trajectory, etc.

The paper proposes a method to identify drivers' driving style and to characterise it with the parameters needed for a simulation model. Besides, this method allows for replicating the actual driver behaviour and elaborating a driving style that can be adopted to develop the CAVs control logic.

Using a driving simulator capable of producing many trials of the same real driver or a group of real drivers for a given road scenario is crucial. CarMaker, the program used to develop the case study of this research, provides this function, and besides this, it can simulate the driving of virtual drivers in the same scenario. In particular, three setting parameters (*Dynamics*, *Energy*, and *Nervousness*) have been used to characterise different virtual drivers.

The case study demonstrated that the proposed method allowed identifying three IVDs, among the 29 simulated, by changing the setting parameters over all possible intervals. These three IVDs have been subsequently used as a reference to cluster the 26 human drivers' records. The attempt to directly cluster the real driver samples was unsuccessful due to the difficulty of interpreting their distribution and assigning descriptive features to the clusters themselves. Conversely, changing each parameter of the IVDs allows the simulation of different driving styles that can be accurately paired with every human driver's behaviour. This opens a series of research opportunities beyond the case study proposed in this paper.

This method is revealed to be straightforward in its application, and its related results can help gather robust examples for training machine learning problems or neural networks. However, building an optimal driving model starting from the referenced IVDs is still an issue.

Future research will focus on analysing traffic, environment, flow control, and road geometry effects on driving style, how random events (like pedestrian or animal crossings) can affect it, and how they must be treated to make outcomes comparable.

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