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Driving Style Recognition based on Ride Comfort Using a Hybrid Machine Learning Algorithm*

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Abstract— **Driving style (DS) classification and identification plays an increasingly important role in the development of advanced driver assistance systems and automated vehicles. Both the enhancement of driving safety and the improvement of fuel efficiency are essential goals of current research in driving style characterization. However, the comfort perspective has still hardly been investigated, despite its importance for the future of driving automation. This paper proposes a driving style classification method, focused on global comfort of the driver and the passengers, but which can also be integrated into the above safety-efficiency viewpoint. Although human comfort in vehicles is affected by different factors, the amplitude and frequency of accelerations are recognized as key signals for assessing driving comfort. The proposed DS classification approach is based on a hybrid machine learning method that combines an unsupervised clustering method with a data-driven extreme learning machine (ELM) algorithm. Hierarchical clustering is used to explore the relevance of the acceleration components in relation to ride comfort, while a single layer ELM topology is implemented to model the DS classifier. The method has been evaluated using experimental data obtained with an instrumented car equipped with in-vehicle sensors and measurement units. The obtained clustering results are consistent with comfort standard indicators, while the data-driven algorithm provides encouraging results: more than 95% classification rate using unseen data.**

I. INTRODUCTION

The recognition of the driving style (DS) of a driver is an ongoing challenge in the context of advanced driving assistance systems (ADAS) and automated driving [1], [2]. The application scope of DS recognition systems includes:

- Driver-style correction systems targeted to improve driving safety, fuel consumption, or both at the same time.
- Personalized ADAS, enhanced with the ability to be adapted to driver behavior.
- Development of control strategies that improve the perceived quality of automated driving.

A complete review of recent research on DS characterization and its relevance for the progress of autonomous vehicles can be found in [1]. Up to now, most of the research focuses on DS analysis concerning two important topics: driving safety and fuel consumption. A variety of techniques and algorithms have been explored to develop DS recognition systems, ranging from simple rule-based algorithms and model-based systems, to sophisticated machine learning methods. Rule-based systems include threshold-based rules, and fuzzy logic rules which are able to adapt to different DS; model-based systems consist of a set of equations whose parameters can be tuned to model different DS; machine-learning algorithms include supervised methods (e.g. shallow and deep artificial neural networks (ANN), support vector machine (SVM), decision trees, etc.), unsupervised methods (e.g. hierarchical clustering analysis (HCA) and principal component analysis (PCA)), and hybrid strategies that combines supervised and unsupervised algorithms.

In addition, data mining techniques for feature selection and feature extraction are extensively used to enhance the performance of machine learning techniques (see [1], and references therein). In previous work, the authors developed a driver recognition system based on driving behavior signals and ANNs. They proposed a high performance system where both the ANN topology (i.e. the number of inputs and the number hidden neurons) and the feature selection are optimized by means of a multiobjective genetic algorithm [3]. A different feature selection approach was proposed in [4], [5], where the nearest shrunken centroids (NSC) clustering procedure [6] was combined with a wrapper around the ANN with the aim of reducing the number of driving behavior signals.

Undoubtedly, safety is the most important objective in the development of unmanned ground vehicles, while energy efficiency is a key factor in the development of environmentally friendly vehicles. However, looking at the humans in this picture [7], comfort and well-being are also significant factors that impact passengers' experience in current as well as future vehicles [8]. It is well known that temperature, smell, gender, age, and many other features have effects on global passenger comfort. Among these, vibrations are considered to be the most significant sources of discomfort (i.e. ride discomfort). One explanation for the connection between discomfort and spectral content is that human organs

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are put under stress when falling into resonance [9], [10]. Although some vibrations are determined by certain characteristics of vehicles and road paving, others depend largely on the driving skills and/or behavior of driver. Therefore, driving style characterization from the comfort perspective is increasingly important in the development of ADAS and automated vehicles [8].

Specifically, the ISO 5805 [11] defines ride comfort as "subjective state of well-being or absence of mechanical disturbance in relation to the induced environment". One of the most unpleasant types of ride discomfort is motion sickness. It is a dizziness, fatigue, or nausea that results from the conflict between visually perceived movement and the vestibular system's sense of movement [8]. So, passengers are more prone to motion sickness than the driver, as they do not maintain visual references.

This paper proposes a driving style classification method, focused on the global comfort of the driver and the passengers, using machine learning techniques. The proposed approach is based on a hybrid machine learning method that combines an unsupervised clustering method with a data-driven extreme learning machine (ELM) algorithm. Agglomerative hierarchical clustering analysis is used to explore the relevance of the acceleration components to ride comfort, while a single layer ELM topology is implemented to model the DS classifier. ELM is a suitable solution, even for demanding applications that require online learning and adaptation [12], [13]. It is based on a simple tuning-free algorithm and its learning speed is very high. Moreover, learning with ELM does not present local minima or overfitting problems. As a consequence, ELM is less dependent on designer intervention than conventional machine learning techniques, such as back-propagation (BP) ANN, or SVM.

The proposed method has been extensively evaluated using experimental data obtained with an instrumented car equipped with sensors and measurement units: the Uyanik car [14]. The DS recognition system provides promising results: more than 95% classification rate using unseen data. Moreover, the DS recognition system has been used to classify a subgroup of drivers that do not participate in the training/testing driving sessions. These experiments provide encouraging results in ride comfort classification and suggest interesting focuses for future investigation. It is worth noting that the proposed implementation approach, based on ELM and driving behavior signals, is able to predict the driving style of a driver along the first minutes of a driving session.

The rest of the paper is organized as follows: Section II introduces the main sources of discomfort in a vehicle, and presents a block diagram of the proposed DS recognition system. In addition, a brief description of the data sets used in this work is provided. Section III introduces the agglomerative hierarchical clustering algorithm used for driving style classification and provides experimental results. After that, in Section IV, the ELM topology is presented and recognition rates are provided. Finally, some concluding remarks are offered and future research work is proposed.

II. RIDE COMFORT CHARACTERIZATION

The discomfort due to vibrations depends on different features: the magnitude, the frequency, the direction, and the duration of the vibrations. Therefore, ride quality evaluation implies considering both discrete events (e.g. an abrupt lane change), and average vehicle motion (e.g. low frequency motion over a long period of time that could induce motion sickness) [10].

Eventual discomfort can be determined by maximum values of acceleration and jerk (i.e. time derivate of acceleration) which typically arise at swift lane changes and entrances and exits of curves. A high value of acceleration or jerk can cause discomfort even during short periods of time. Concerning average vehicle motion, low frequency motion is the main contributor to motion sickness, while high frequency motion causes stress and discomfort. Motion sickness is rarely a problem at high frequencies.

There are different methods for quantifying ride quality from comfort perspective. As is detailed in [9], [10], the sensation of vibrations on human body depends on the signal direction and its spectral content, and accordingly, inspection of the Power Spectral Density (PSD) is a powerful method for the evaluation of ride quality. The PSD of a signal provides a measure of the power present in the signal as a function of frequency, per unit frequency. In most practical applications, it can be estimated by computing the squared magnitude of the Fourier transform. In addition, the International Organization for Standardization (ISO) 2631-1 defines several methods to measure vibrations as well as to process data to standardized performance measures concerning health, perception, comfort and motion sickness [15]. The quantified performance measures of ISO 2631 are based on frequency weighted root mean square (RMS) computations of acceleration data in each axis. The ISO norm defines several filter shapes that delimit the frequency bands where different components of discomfort are present: filters w_f, w_d, and w_k, where filter w_f is representative of motion sickness discomfort, while the filters w_d and w_k model the horizontal and vertical components of global discomfort, respectively (see Fig. 1).

Most of the above methods for evaluating ride comfort/discomfort consider a single frequency, or a limited frequency range, and a single direction. However, taking into account that passengers are exposed to multiple frequencies in different axes at the same time, it can be conjectured that motion at many different frequencies and directions might increase the discomfort and the risk of motion sickness. Therefore, a classification of driving styles based on ride comfort should consider the total power of vibrations, independently of the kind of discomfort that each frequency/axis generates.

A. Development of the Driving Style Recognition System

The block diagram depicted in Fig. 2 shows the main steps involved in the development of the proposed DS recognition system. It is based on a hybrid machine learning method that

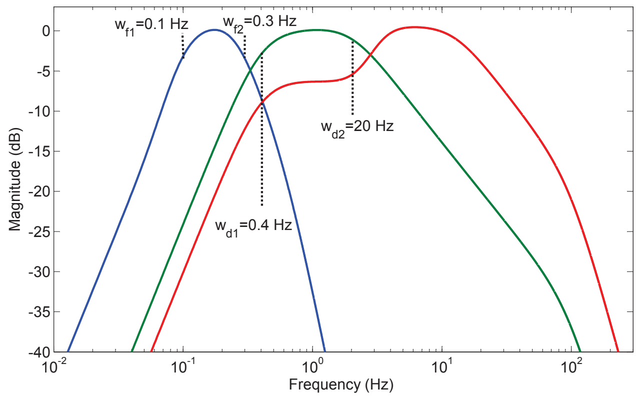

Fig. 1. Amplitude responses of different weighting filters in ISO 2631, w_f: motion sickness (blue), w_d: global comfort horizontal-component (green), and w_k: global comfort vertical-component (red).

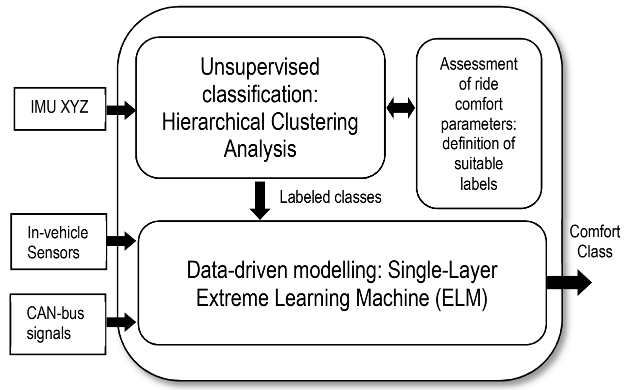

Fig. 2. Block scheme: development process of the hybrid DS characterization system for ride comfort classification.

combines an unsupervised clustering algorithm with a data-driven extreme learning machine. Firstly, the driving styles of a group of drivers are classified into a number of discrete classes based on selected features: a hierarchical clustering algorithm is used in this step. Since our aim is to classify the drivers according to the ride comfort of their driving styles, the summation of the spectral components (i.e. PSD sum) of accelerations in each axis is selected as input feature. This feature accounts for ride comfort in a broad sense, and a typical inertial measurement unit (IMU) attached to the vehicle can be used to capture the XYZ accelerations.

Then, each class is to be labeled according to a predefined comfort criterion: the evaluation of meaningful comfort parameters, or the result of a survey filled in by the passengers. A combined approach, that considers both criteria would be desirable. However, in this work, the former approach will be used because passengers' surveys are not available.

After that, a DS recognition system is developed to model the classifier. Extreme learning machines (ELM) with a variety of architectures have been evaluated to implement the classifier: single-layer ELM, ELM auto-encoders, and deep-ELM [13]. The best performance has been obtained with a single layer feed-forward network (SLFN) featuring 100 neurons in the hidden layer. This topology has been selected to carry out the experiments presented in the following sections. The whole method has been evaluated using experimental data obtained with the Uyanik instrumented car [14].

B. The Uyanik Data Set

The data set was collected using the Uyanik instrumented car: a sedan car equipped with different sensors and measurement units [14]. The car route is around 25 km, about 40 minutes, in the vicinity of Istanbul. It includes different kinds of roads and traffic sections: city, very busy city, highway, highway with less traffic, and a university campus. A representative subset of the recording sessions consisting of 22 drivers was chosen, recordings with missing values or incomplete information were discarded. The complete data set includes audio and video recordings, CAN-bus signals, pedal-sensor recordings, a frontal laser scanner, and an inertial measurement unit (IMU).

After a comprehensive examination of the available information, a set of signals and variables, which are successfully used for modeling driving behavior, was selected [5]. The subset of low level variables (i.e. time series), and 20 high level features (RMS value (time domain), and PSD sum (frequency domain)) used in this research is summarized in Table I. Several redundant variables, such as: roll rate, pitch rate and yaw rate, were discarded because they do not improve the driving comfort classification rates obtained with the selected signals. The sample rate of the signals is 32 Hz and the features are computed over 128-second frames (i.e. 4096 samples) with 1-second shift (i.e. 32 sample shift), that is to say, with an overlapping of 127 seconds between consecutive windows. The acceleration: XACC, YACC, and ZACC, will be used in the development and subsequent labeling of the ride comfort classes, while the remaining features will be used to implement the DS recognition system.

The driving session of each driver was partitioned into a training segment (approximately two thirds of total trip: around 1600 windows) and a testing segment (the remaining third of the trip without window overlapping: around 672 windows). A subgroup of 15 drivers was involved in the development of the DS recognition system, while 7 drivers without previous contact with the system were used to evaluate the performance of the ELM-based classification model.

III. DRIVING STYLE CLASSIFICATION INSPIRED FROM COMFORT PERSPECTIVE

An agglomerative Hierarchical Cluster Analysis (HCA) has been used to establish coherent groups of drivers based on the input features in the training data of every driving session. This is a bottom-up approach that iteratively measures the distance between any two clusters (initially single drivers) merging the two closest ones in each step. The measurement method in this case considers the Euclidean distance and

TABLE I

DRIVING STYLE RECOGNITION: SENSORS, SIGNALS AND FEATURES

Sensors and units	Signals (time series: 32 Hz sample rate)	Time (RMS)	Frequency (PSD sum)
CAN-bus	SWA: Steering wheel angle	1	11
	SWS: Steering wheel speed	2	12
	VS: Vehicle speed	3	13
	PGP: Percent gas pedal	4	14
	ERPM: Engine RPM	5	15
Pressure sensors	BP: Break pedal pressure	6	16
	GP: Gas pedal pressure	7	17
IMU unit	XACC: X axis accelerometer	8	**18**
	YACC: Y axis accelerometer	9	**19**
	ZACC: Z axis accelerometer	10	**20**

High level features are derived from analysis frames of 128 sec with an overlapping of 127 sec. Only signals in boldface are involved in the clustering step.

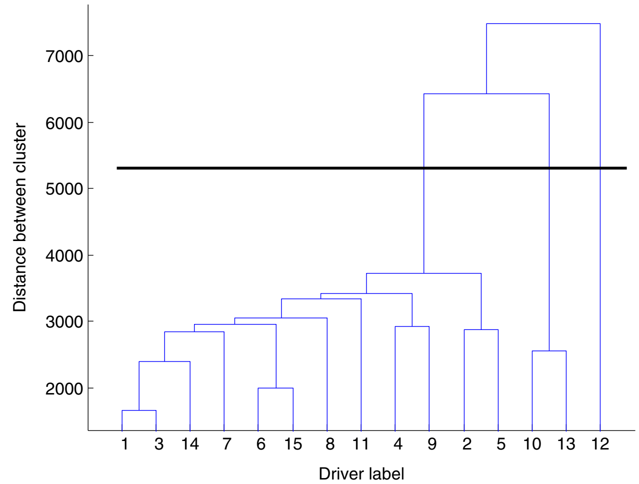

Fig. 3. Dendrogram corresponding to the categorization of the first 15 drivers into homogeneous classes from the perspective of ride comfort.

follows a single-linkage algorithm (i.e. nearest neighbor). It evaluates the distance between the closest members of each pair of clusters. This unsupervised clustering procedure generates a hierarchical structure in the form of a binary tree.

The input to the HCA is the RMS of the PSD sum of the accelerations in each axis (XACC, YACC, ZACC). The available data are sampled at 32 Hz, so, according to Nyquist Criterion, the frequency analysis is limited to less than 16 Hz, meanwhile low frequency components that lay out of the frequency band $w_f \cup w_d \cup w_k$ are discarded because they are little relevant for ride comfort characterization (see Fig. 1). It is worth noting that each part of the human body has a natural resonance frequency, some of which lie above 16 Hz (e.g. the head natural frequency) [17]. However, most of the analysis performed on biomechanical models state that the response of the human body vibration is relevant until 10 Hz, and from this point it begins to lose sensitivity linearly [18]. This behavior is consistent with the filters proposed in the 2631-1 ISO (see Fig. 1).

A. HCA Experimental Results

The HCA method has been used to categorize the first 15 drivers into homogeneous classes from the perspective of ride comfort. The obtained binary tree is depicted by the dendrogram in Fig. 3, where the vertical axis represents the dissimilarity between clusters, and thus, the horizontal line in the picture shows three well-distinguished clusters. On the right of the figure it can be clearly seen a single-driver class (Cluster 1) associated with Driver 12; on the left side of the figure a class composed of 12 drivers, the most populated class, can be distinguished (Cluster 2); finally, the third cluster matches up Driver 10 and Driver 13 (Cluster 3). Figure 4 shows the values of the statistical variables used to develop the clusters, the members of each cluster are highlighted using different symbols and colors. The number of clusters has been selected taking into account a trade-off between classification discrimination and complexity. As will be seen next, both the results shown in the dendrogram as well as the interpretability of the clusters confirm the suitability of a three-class DS classifier.

B. Classes Analysis using Comfort Parameters

In the following, the previously developed classes will be labeled inspired from ride comfort. As it has been introduced in Section II, there are several methods for quantifying ride quality. Two widely accepted indices will be used to analyze the obtained clusters and assign suitable labels to each class.

Each performance measure is related to a specific frequency filter (see Fig. 1). The first comfort parameter that will be evaluated is the total weighted RMS acceleration (a_v) [16]. It considers the acceleration signal in three axes

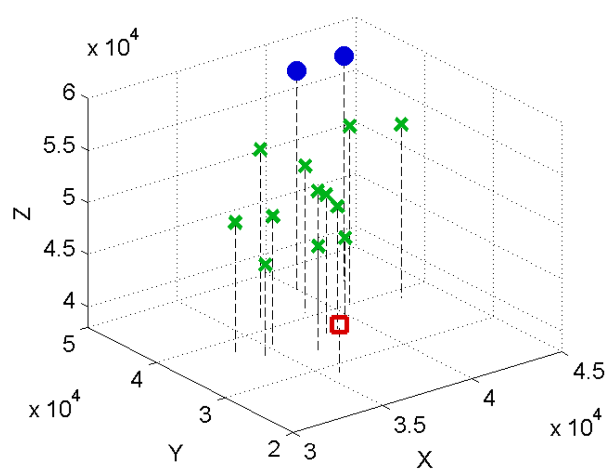

Fig. 4. Input data to the agglomerative HCA: RMS(PSD sum) of accelerations. Selected clusters are: Cluster 1 (blue dot): Drivers 10 and 13; Cluster 2 (green cross): Drivers 1-9. 11, 14, and 15; Cluster 3 (red square): Driver 12.

and reflects the effect of signal spectral content in the human body as the 2631-1 ISO determines. This parameter is defined as follows:

$$a_v = \sqrt{k_x^2 a_{wxd}^2 + k_y^2 a_{wyd}^2 + k_z^2 a_{wzk}^2}, \quad (1)$$

where k_x, k_y and k_z are constants according to [15] that quantify the effect of the different axes accelerations in the human body. Furthermore, the accelerations are weighted and filtered in the way that the same ISO norm determines, and a_{wxd}, a_{wyd} and a_{wzk} are the results of being filtered by w_d, w_d and w_k filter, respectively (see Fig. 1). The weighted RMS acceleration for each axis is expressed as,

$$a_{wij} = \sqrt{\frac{1}{T_f}\int_0^{T_f} a_i^2, w_j(t)dt}, \quad (2)$$

where i determines the direction, j is the corresponding filter, and T_f is the time range of acceleration data.

In the same standard, a measure of the likelihood of nausea (MSDV) due to motion sickness is defined and quantified. MSDV is accumulated over time. Although, it may also be useful to evaluate the mean MSDV-rate, which is independent of the time range of the measurement:

$$MSDV_i = \sqrt{\frac{1}{T_f}\int_0^{T_f} a_i^2, w_f(t)dt}, \quad (3)$$

where w_f is the blue filter in Fig. 1.

The above performance index (1) and (3) have been computed for each driver that participated in the driving sessions. The first index, a_v, represents a general comfort measure and the second one, MSDV, is related with motion sickness. In view of the obtained results (see Fig. 5), it can be concluded that the hierarchical clustering analysis performed in the previous section is representative of the ride comfort of each one of the 15 drivers. Moreover, comparing the results of a_{wij} with the values specified in ISO 2631-1 for each axis [10], likely reactions of the passengers for all the drivers under test would be rather comfortable (Cluster 1), a little uncomfortable (Cluster 2), or, in the worst situation (Cluster 3), fairly uncomfortable. It is worth noting that none of the drivers exhibits very uncomfortable driving behavior, therefore, current data are not able to account for a richer specter of driving styles. Regarding MSDV, the results clearly highlight the different driving styles, in agreement with the previous ones. In sum, a suitable label assignment could be: Cluster 1: “Comfortable”, Cluster 2: “A Little Uncomfortable”, and Cluster 3: “Fairly Uncomfortable”.

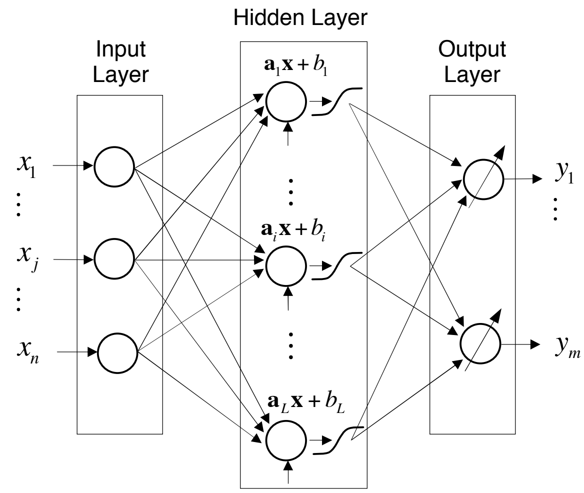

Fig. 6. Topology of a single-layer feed-forward network (SLFN) used by ELM. The weights and biases of the hidden layer are random numbers, while the parameters of the output layer are analytically determined.

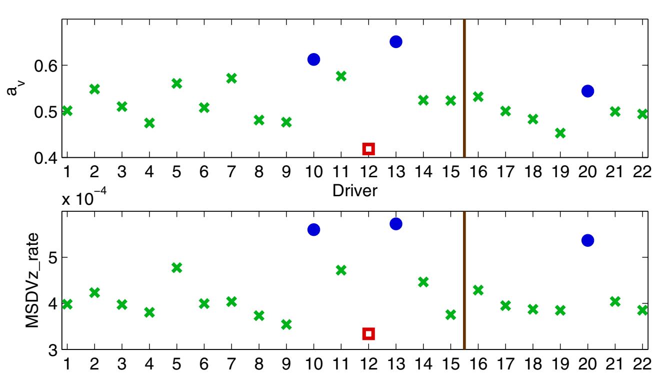

Fig. 5. Ride quality from comfort perspective quantification. Top: a_v parameter, which describes general comfort; bottom: $MSDVz\_rate$ parameter, which is related with motion sickness. The drivers on the left side of the vertical line (1 to 15) were used to train the system, while the drivers on the right side (16 to 22) are new for the DS classifier.

IV. COMFORT-BASED DRIVING STYLE RECOGNITION USING ELM

The implementation of the DS classification developed in Section III will be performed using a SLFN ELM with 100 neurons in the hidden layer. The advantages of ELM-like algorithms arise from the fact that the parameters of the hidden nodes are randomly generated and do not need to be iteratively tuned [12], [13]. As a consequence, the learning procedure of ELM is simpler and less time-consuming than conventional learning algorithms such as backpropagation-ANN and SVM.

A. *Extreme Learning Machine*

First, the basics of ELM are briefly reviewed with the aim of highlighting the advantages of this machine learning technique and providing the required background. Fig. 6 depicts the topology of a SLFN with n inputs, m outputs, and L nodes in the hidden layer. The network output for generalized batch ELM with additive nodes is

$$y(\mathbf{x}) = \sum_{i=1}^{L} \beta_i h_i(\mathbf{x}) = \mathbf{h}(\mathbf{x})\boldsymbol{\beta}. \quad (4)$$

Without loss of generalization, a single output node ($m = 1$) is taken in (4). The vector of weights $\boldsymbol{\beta} = [\beta_1, \cdots, \beta_L]$

links the hidden nodes (i.e. random nodes) with the output node, and $\mathbf{h}(\mathbf{x}) = [h_1(\mathbf{x}), \cdots, h_L(\mathbf{x})]$ is the output vector of the hidden layer for a given input $\mathbf{x} \in \mathbf{R}^n$. The output of the ith hidden node is

$$h_i(\mathbf{x}) = s(\mathbf{a}_i\mathbf{x} + b_i), \mathbf{a}_i, \mathbf{x} \in \mathbf{R}^n, \mathbf{b}_i \in \mathbf{R}, \tag{5}$$

with $s(\mathbf{a}_i\mathbf{x}+b_i)$ being the sigmoid activation function, $\mathbf{a}_i$ the random weights vector connecting the inputs with the ith hidden node, and b_i the random bias of the ith hidden node. The set of parameters of the hidden nodes $(\mathbf{a}_i, b_i)$, with $1 \leq i \leq L$, are randomly generated and they are not tuned.

Learning aims at computing the vector of output weights, $\boldsymbol{\beta}$ in (4), for each output node. Given a set of K training samples, $(\mathbf{x}_j, \mathbf{t}_j), 1 \leq j \leq K$, where $\mathbf{x} \in \mathbf{R}^n$ is the jth input vector, and $\mathbf{t} \in \mathbf{R}^m$ is the corresponding output vector (i.e. the target output), learning is performed by solving (4) for the set of training samples

$$\mathbf{T} = \mathbf{H}(\mathbf{x})\mathbf{B}, \tag{6}$$

with $\mathbf{H}$ being the hidden layer output matrix

$$\mathbf{T} = \begin{bmatrix} \mathbf{h}(\mathbf{x}_1) \\ \vdots \\ \mathbf{h}(\mathbf{x}_K) \end{bmatrix} = \begin{bmatrix} h_1(\mathbf{x}_1) & \cdots & h_L(\mathbf{x}_1) \\ \vdots & \vdots & \vdots \\ h_1(\mathbf{x}_K) & \cdots & h_L(\mathbf{x}_K) \end{bmatrix}_{K \times L} \tag{7}$$

$$\mathbf{B} = \begin{bmatrix} \boldsymbol{\beta}_1 & \ldots & \boldsymbol{\beta}_m \end{bmatrix}, \text{ and } \begin{bmatrix} \mathbf{t}_1 \\ \vdots \\ \mathbf{t}_K \end{bmatrix}_{K \times m} \tag{8}$$

Then, (6) is a linear system and the output weights $\mathbf{B}$ can be estimated as

$$\hat{\mathbf{B}} = \mathbf{H}^\dagger \mathbf{T}, \tag{9}$$

where $\mathbf{H}^\dagger$ is the Moore Penrose generalized inverse of matrix $\mathbf{H}$. Different methods can be used to solve (9), with the singular value decomposition (SVD) method being the most used with ELM [19].

B. Experimental Results

The DS recognition system has been extensively tested using the selected features and the Uyanik data set (see Table I). The whole group of 15 drivers used to train the system has been evaluated with the aim of verifying the performance of the ELM classifier. In this evaluation, two thirds of the data were intended to train the system, and the remaining one third was saved for testing. The ELM training and prediction are performed over the subset of input features (i.e. features 1 to 7 (time domain) and 11 to 17 (frequency domain)), with 100 hidden neurons, L=100. In every case, the average accuracy over 100 trials of ELM has been computed to provide more stable results and minimize the effect of randomness. The mean ride comfort class identification rate for the 15-driver group, is 93.57% with a standard deviation of 0.99 and a maximum identification rate of 95.71%. The above topology provides a performance versus complexity trade-off: a smaller network could be used without significant degradation of results (e.g. the mean identification rate is 91.80% with L=50 and 90.84% with L=30), while an increase in the the number of hidden neurons scarcely improves the identification rates.

On the other hand, the ELM paradigm has been compared with a traditional classification technique: the Support Vector Machine (SVM) with radial basis function (RBF) kernel [20]. The cost parameter C has been chosen equal to the range of output values of training data, i.e. $C = 1$, while the RBF kernel parameter γ has been selected from the best performance of $\gamma = \left[2^{-7}, 2^{-6}, \cdots, 2^{7}\right]$. According to our experimental results, SVM is able to slightly improve the generalization performance of SLFN ELM: the best ride comfort class identification rate, for the 15-driver group, is 97.86%. This value has been obtained with $\gamma = 2^{-2}$. However, the SVM system requires as much as 1495 support vectors (i.e. nodes) to achieve a 2% improvement. Fine tuning around the above values increases the identification rate up to 98.03% with $\gamma = 0.35$ and 1673 support vectors. In sum, the performance of SVM is slightly better than the performance of ELM, but at the expense of a complexity increase of more than one magnitude order.

Table II summarizes the classification rates obtained using the last third of each driving session to test the ELM. As can be seen, the ELM-based system is able to model the DS of the whole group of 15 drivers. Every driver have been successfully classified using the testing data. The testing data were obtained during the same driving session as the training data, but in a different segment of the route, this fact validates the robustness of the proposed method.

The developed DS classification system has been used to classify a subgroup of 7 drivers who do not participate in the previous training/testing of the system (i.e. unseen drivers). These drivers traveled the same route as the drivers used to develop the system. Table III presents the classification rates for each unseen driver. As can be seen, six of the seven drivers have been classified into Cluster 2 ("A Little Uncomfortable"), while Driver 20 has been classified into Cluster 1 ("Fairly Uncomfortable").

With the aim of getting a deeper insight into the classifier operation, the selected comfort index (1) and (3), corresponding to the 7-driver group have been evaluated (see Fig. 5). In view of these results, Driver 20 should be also classified into Cluster 2. However, a more comprehensive analysis of this driver revealed that he/she presents high values of accelerations in Y axis (YACC: lateral axis). This component of acceleration (lateral acceleration) resulting from driver's turning paths is a relevant cause of motion sickness for passengers [21]. In addition, we observed that the driving session of this driver was affected by traffic jam (more than 10 minutes). Although the fraction of the path affected by traffic jams was excluded from the testing data, this fact could have affected negatively the driving style of the driver. In this sense, DS classification contemplates more than one style for the same driver under different conditions.

V. CONCLUSIONS

A new driving style classification method, focused on ride comfort of the driver and passengers, has been proposed. Although driving safety and fuel efficiency are typical goals in current driving style recognition systems, ride comfort has attracted little research attention, despite its significance for future unmanned ground vehicles.

A hybrid machine learning method has been developed and successfully tested using experimental data. The system, composed of an unsupervised hierarchical clustering analysis (HCA) algorithm and a high performance extreme learning machine (ELM), takes advantage of recent advances in machine learning and data mining. This kind of hybrid approach improves the overall performance of the system, and is suitable for further improvement of the classification accuracy by increasing the number of input features. Moreover, other goals of interest (e.g. safety or fuel efficiency) could be easily integrated into the classifier by means of a clustering redefinition and ELM retraining.

Our experimental results show that the HCA algorithm is able to identify relevant clusters that can be coherently interpreted from the ride comfort perspective. In addition, the ELM network provides high classification rates, more than 95%, using a straightforward single-layer topology. The robustness of the method has been evaluated by means of new drivers that did not participate in the development of the system. Most of these drivers were successfully classified, according to the values of standard comfort indices. However, complementary information about the driving sessions and the passengers' experience is required to obtain more reliable conclusions: this is the aim of our future research.

TABLE II
EXPERIMENTAL RESULTS USING THE 14-100-3 ELM TOPOLOGY

Driver	**Target Cluster**	**Percentage Classification (%)**		
		Cluster 1	***Cluster 2***	***Cluster 3***
10	1	83.70	16.30	0.00
13	1	67.00	32.48	0.00
1	2	0.00	100.00	0.00
2	2	0.00	100.00	0.00
3	2	0.00	100.00	0.00
4	2	0.00	100.00	0.00
5	2	0.00	100.00	0.00
6	2	0.14	99.86	0.00
7	2	12.71	87.29	0.00
8	2	5.18	94.82	0.00
9	2	0.23	99.77	0.00
11	2	0.00	100.00	0.00
14	2	3.61	96.39	0.00
15	2	1.16	98.84	0.00
12	3	0.00	0.00	100.00

Test results obtained using the last third of each trip.

TABLE III
EXPERIMENTAL RESULTS FOR UNSEEN DRIVERS

Driver	**Output Cluster**	**Percentage Classification (%)**		
		Cluster 1	***Cluster 2***	***Cluster 3***
16	2	0.00	100.00	0.00
17	2	0.00	100.00	0.00
18	2	3.53	96.47	0.00
19	2	10.32	89.68	0.00
20	1	65.51	34.49	0.00
21	2	0.00	100.00	0.00
22	2	0.00	100.00	0.00

REFERENCES

[1] C. Marina Martinez, M. Heucke, F. Y. Wang, B. Gao and D. Cao, "Driving Style Recognition for Intelligent Vehicle Control and Advanced Driver Assistance: A Survey," in IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 3, pp. 666-676, March 2018.

[2] Y. Du, C. Liu and Y. Li, "Velocity Control Strategies to Improve Automated Vehicle Driving Comfort," in IEEE Intelligent Transportation Systems Magazine, vol. 10, no. 1, pp. 8-18, Spring 2018.

[3] J. Echanobe, I. del Campo and M. V. Martnez, "Design and optimization of a Neural Network-based driver recognition system by means of a multiobjective genetic algorithm," 2016 International Joint Conference on Neural Networks (IJCNN), Vancouver, Canada, 2016, pp. 3745-3750.

[4] M. V. Martnez, I. del Campo, J. Echanobe and K. Basterretxea, "Driving Behavior Signals and Machine Learning: A Personalized Driver Assistance System," 18th IEEE International Conference on Intelligent Transportation Systems (ITSC), Las Palmas Gran Canaria, Spain, 2015, pp. 2933-2940.

[5] M. V. Martnez, J. Echanobe and I. del Campo, "Driver identification and impostor detection based on driving behavior signals," 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, Brazil, 2016, pp. 372-378.

[6] R. Tibshirani, T. Hastie, B. Narasimhan, and G. Chu, "Class Prediction by Nearest Shrunken Centroids, with Applications to DNA Microarrays," Statistical Science, vol. 18, pp. 104-117, 2003.

[7] E. Ohn-Bar, and M. M. Trivedi, "Looking at Humans in the Age of Self-Driving and Highly Automated Vehicles," IEEE Transactions on Intelligent Vehicles, vol. 1, no. 1, pp. 90-104, 2016.

[8] M. Elbanhawi, M. Simic, and R. Jazar, "In the passenger seat: Investigating ride comfort measures in autonomous cars," IEEE Intelligent Transportation Systems Magazine, vol. 7, no. 3, pp. 417, Fall 2015.

[9] N. Karlsson and H. Tjärnbro, Motion sickness in cars, Department of Product and production Development. CHALMERS UNIVERSITY OF TECHNOLOGY, 2012.

[10] J. Eriksson and L. Svensson, "Tuning for Ride Quality," in Autonomous Vehicle, UPPSALA UNIVERSITET, 2015.

[11] ISO, Vibration and Shock-Vocabulary, ISO 2041, 1990.

[12] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme Learning Machine for Regression and Multiclass Classification," IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics, vol. 42, no. 2, pp. 513-529, 2012.

[13] J. X. Tang, C. W. Deng, and G. B. Huang, "Extreme Learning Machine for Multilayer Perceptron," IEEE Transactions on Neural Networks and Learning Systems, vol 27, no. 4, pp. 809-821, 2016.

[14] H. Abut, H. Erdogan, A. Ercil, B. C Çürüklü, H. C. Koman, F. Tas, A. O. Argunsah, S. Cosar, B. Akan, H. Karabalkan, E. Cokelek, R. Ficici, V. Sezer, S. Danis, M. Karaca, M. Abbak, M. G. Uzunba, K. Eritmen, M. Imamolu, and C. Kalaycoglu, Real-World Data Collection with UYANIK. Springer US, 2009, ch. 3, pp. 2344. [Online]. Available: http://http://www.es.mdh.se/publications/2852-Real World Data Collection with UYANIK.

[15] Mechanical Vibration and Shock-Evaluation of Human Exposure to Whole-Body Vibration-Part 1: General Requeriments. International Organisation for Standaisation 2631-1, 1997.

[16] J. C. Castellanos and F. Fruett, ”Embedded system to evaluate the passenger comfort in public transportation based on dynamical vehicle behaviour with user's feedback,” Measurement, vol. 47, pp. 442-451, 2014.

[17] S. Badran, A. Salah, W. Abbas, and O.B. Abouelatta, ”Design of Optimal Linear Suspension for Quarter Car with Human Model using Genetic Algorithms,” The Research Bulletin of Jordan ACM, vol. II, pp. 42-51, 2012.

[18] S. Kitazaki, and M.J. Griffin, ”A Modal Analysis of Whole-Body Vertical Vibration Using a Finite Element Model of the Human Body,” Journal of Sound and Vibration, vol. 200(1), pp. 83-103, 1997.

[19] W. H. Press, S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery, Numerical Recipes. The Art of Scientific Computing, third edition, Cambridge University Press, 2007.

[20] C. Cortes, and V. Vapnik, ”Support vector networks,” Machine Learning, vol. 20, n 3, pp. 273-297, 1995.

[21] M. Turner and M. J. Griffin, ”Motion sickness in public road transport: The effect of driver, route and vehicle,” Ergonomics, vol. 42, pp.1646-1664, 1999.