Driver Behavior Profiling based on Efficient Recurrence Quantification Analysis

DANUT DRAGOS DAMIAN[1], SIMONA MOLDOVANU[2], FELICIA ANISOARA DAMIAN[3], ION ION[4], LUMINITA MORARU[1,5]
[1] The Modelling & Simulation Laboratory, Dunarea de Jos University of Galati, Galati, ROMANIA
[2] Department of Computer Science and Information Technology, Faculty of Automation, Computers, Electrical Engineering and Electronics, Dunarea de Jos University of Galati, Galati, ROMANIA
[3] Emil Racovita High School of Galati, Galati, ROMANIA,
[4] Research Centre for Thermal Machinery and Environmental Engineering in Energy – METIME, Dunarea de Jos University of Galati, Galati, ROMANIA
[5] Department of Physics, School of Science and Technology, Sefako Makgatho Health Sciences University, Pretoria, SOUTH AFRICA

Abstract: - Following the hypothesis that nonlinear dynamics provide a more sensitive description of driving variability compared to conventional linear metrics, we investigate whether nonlinear dynamic measures derived from recurrence quantification analysis (RQA) can effectively reveal and quantify recurrent driver behavior from inertial sensor data (accelerometer and gyroscope signals). Recurrence plots (RPs) of tri-axial accelerometer and gyroscope data facilitate recurrence quantification analysis (RQA) by using recurrence rate (RR), determinism (DET), entropy (ENTR), laminarity (LAM), trapping time (TT), and line-based metrics. The cross-recurrence quantification analysis (CRQA) is used to identify multivariate correlations among sensor data. These data could be used in intelligent transportation systems, driver assistance technology, and safety surveillance. The results hold potential applications in intelligent transportation systems, driver assistance technologies, and safety monitoring. The ability of CRQA to capture inter-signal dependencies further opens possibilities for multimodal driver monitoring frameworks.

Key-words: Recurrence Plots (RPs), Recurrence Quantification Analysis (RQA), cross-recurrence quantification analysis (CRQA), driver behaviour.

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1 Introduction

A responsible driving style characterised by alertness and adherence to speed limits is fundamental to reducing road accidents and saving lives. This driving style should complement various safety technologies, such as autonomous emergency braking, lane-keeping, or pedestrian detection systems, which the European Union mandates under EU Regulation 2019/2144 devoted to the General Safety Regulation [1]. Ongoing driver education ensures that drivers remain informed about emerging risks, updates to traffic laws, and the capabilities and limitations of vehicle technologies. Road traffic accidents remain one of the leading causes of death worldwide, claiming around 1.19 million lives each year. According to the World Health Organization (2023), approximately 12% of these deaths are linked to driver inattention [2]. These combined efforts are aligned with the European Commission's Vision Zero strategy, which aims to eliminate fatalities and serious injuries on European roads by 2050, as well as with the United Nations' Global Plan for the Decade of Action for Road Safety 2021–2030 [3].

Understanding driver behaviour is crucial for developing intelligent transportation systems, road safety frameworks, and adaptive vehicle technologies. Traditional approaches rely on statistical or linear metrics that capture average patterns but fail to fully represent the complexity and diversity of human behavior. Nonlinear interactions among vehicle control, environmental factors, and individual decision-making significantly influence driving dynamics, highlighting the need for analytical tools that account for these intricate relationships. RPs and RQA offer robust methods for identifying dynamical invariants in complex time series data. RQA quantities as determinism, entropy, and laminarity used to describe the stability, variability, and transitional nature of system dynamics. These nonlinear descriptors outperform conventional metrics in detecting structured yet irregular variations in accelerometer and gyroscope signals, making them well-suited for applications like driver profiling. Ashqar et al. [4] utilized RQA features derived from accelerometer, gyroscope, and rotation vector data to classify vulnerable road users, achieving high accuracy and demonstrating RQA's effectiveness in real-world mobile sensing contexts. Marwan and Kraemer [5] provided an extensive overview of recent developments in recurrence-based methods, including parameter optimization, multiscale and heterogeneous recurrences, novel quantifiers, and their integration with machine learning techniques. Similarly, Karrouchi et al. [6] analyzed driving parameters—such as engine speed, vehicle speed, accelerator pedal position, steering wheel angle, engine noise intensity, fuel consumption, and exhaust gas volume—to assess driver behavior. They plotted curves of each factor over time and defined limits for each driving style, as well as some limits for conscious driving. The RP method offers significant benefits in time-series analysis by visualization of the recurrent states [7, 8]. Traditional linear time series analysis methods are often limited in practical applications due to the nonlinear and nonstationary nature of time series data generated by complex systems. In contrast, the RP method does not rely on assumptions about data stationarity, distribution, or a minimum number of observations. This makes RPs a more flexible and effective tool for analyzing short or irregular time series [9]. This paper examines whether nonlinear dynamic measures derived from RQA offer a sensitive and reliable framework for profiling driver behaviour based on inertial sensor data. They can reveal structured dynamic patterns in driving data that linear descriptors fail to detect, enhancing the ability to distinguish between different driving behaviors and conditions. While univariate RQA captures dynamics along individual axes, driver behavior is influenced by interactions among multiple sensor modalities. Thus, we address the Cross-Recurrence Quantification Analysis (CRQA) to identify and analyse the synchronization and coupling between accelerometer and gyroscope signals [10]. The multivariate perspective provides a more comprehensive view of the underlying processes.

This approach is based on information from the devoted database [11]. Statistical analysis is conducted to determine the significance of operational characteristics in profiling driving behavior. The proposed solution offers an effective means to study driving behavior.

The main contributions of this study are: (i) Development of a recurrence-based framework for analyzing inertial signals of driver behavior; (ii) Integration of both univariate RQA and CRQA multivariate techniques; (iii) By positioning driver behavior as a nonlinear dynamic process, this work advances the methodological toolkit available for traffic safety research and human–machine interaction studies.

2 Problem Formulation

This paper aims to conduct a thorough analysis of the recorded data from inertial measurement units to determine driving style. A statistical analysis of eight parameters extracted from RPs is performed. Figure 1 describes the structure of the proposed approach and its blocks.

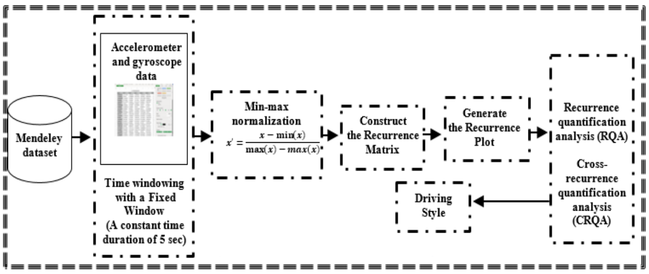

Fig. 1. Flowchart of this study

2.1 Recurrence Plot (RP)

An RP reveals both large-scale patterns and small-scale structures, including isolated points. Time-series data are described mathematically as $\{x(t)\}_{t=0}^{T}$ observations recorded sequentially over time. RPs expose all the recurrent states of a dynamical system [7], $\vec{x}_i=[x(t_i)+x(t_i+\tau)+\ldots+x(t_i+(m-1)\tau]$. An RP is a two-dimensional binary matrix,

$$R_{ij}=\Theta(\epsilon-\|\vec{x}_i-\vec{x}_j\|) \tag{1}$$

Θ denotes the Heaviside function, ϵ is the recurrence threshold, $\|\cdot\|$ is a norm, τ is the time delay, and m is the embedding dimension. The recurrence threshold ϵ is a critical parameter for an accurate RP [12, 13]. The literature suggests that a threshold ϵ of 0.1 is used in most circumstances [14]. A recurrence matrix R_{ij} is plotted as a binary RP image, where black (1) indicates recurrence or similar states, while white (0) shows no recurrence. To visualise dynamic patterns using RPs, driving data is segmented into discrete time intervals using a fixed time-windowing technique in order to facilitate the identification of trends within each time window. This approach simplifies the data, enables the detection of short-term temporal patterns that are valuable for profiling driver behavior and identifying anomalies, and helps reduce dimensionality. Consequently, an RP reveals both large-scale patterns and finer structures, such as isolated points, diagonal, vertical, and horizontal lines. Vertical and horizontal lines imply deterministic dynamics, with periods of similar state revisits across time. Near isolated points, it may suggest chaotic behaviour. Periodic diagonal lines indicate unstable periodic orbits. The intersection of vertical and horizontal lines forms rectangular clusters of recurrence points. White bands indicate nonstationary behaviour, suggesting rare or unusual states or a transition between regimes. Diagonal lines indicate how states similarly change throughout time. Long, continuous diagonals indicate deterministic or predictable behavior. Shorter diagonals signify laminar states, i.e., the system remains quasi-stationary or undergoes gradual changes [15, 16].

2.2 Recurrence Quantification Analysis (RQA) and Cross-Recurrence Quantification Analysis (CRQA)

As the RPs focus on trends and possible rules not on individual data points, eight RQA measures are used to analyse texture features in RPs [17, 18]. RQA turns visual patterns in RPs into measurable data. A generated cross-recurrence plot (CRP) has the following meaning: a (i, j) point showing that the state of the acceleration system at time i is the same as the state of the gyroscope system at time j. Both systems are in sync across time, have a lag, and share dynamics.

(1) Recurrence rate (RR) reveals the dynamic changes in a system:

$$RR=\frac{1}{N^2}\sum_{i,j} R_{ij} \tag{2}$$

High RR values reveal repetitive behavior; lower RRs indicate more unpredictable driving. CRQA determines the proportion of shared states.

(2) Determinism (DET) measures the predictability and deterministic structure in a system:

$$DET=\frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} lP(l)}\text{, with} \tag{3}$$

$$P(l)=\frac{\text{No of diagonal lines of length } l}{\text{Total number of diagonal lines}}$$

Higher DET indicates predictable and controlled driving behavior. Short diagonal lines or a lower DET show random occurrences or noise, driving patterns are irregular, indicating a possible distraction or tiredness. CRQA indicates that shared dynamics are predictable.

(3) Average diagonal line length (Mean L):

$$\text{Mean L}=\frac{\sum_{l=l_{min}}^{N} lP(l)}{\sum_{l=1}^{N} P(l)} \tag{4}$$

is the average time that two segments of the trajectory approach each other. A higher Mean L shows more predictability and less noise; a lower Mean L suggests a more chaotic or noisy system. CRQA-mean predictability or stability of trajectories

(4) Entropy (ENTR) reflects the complexity of an RP for the diagonal lines:

$$ENTR=-\sum_{l=l_{min}}^{N} P(l)\log P(l) \tag{5}$$

High ENTR suggests complex, diverse system behavior, such as mixed driving styles; low ENTR suggests simpler, more repetitive, or regular behavior CRQA indicates variability of synchronization patterns.

(5) Laminarity (LAM) helps detect stop-and-go behaviour:

$$LAM=\frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=1}^{N} vP(v)}\text{, with} \tag{6}$$

$$P(v)=\frac{\text{Total number of vertical lines}}{\text{Number of vertical lines of length v}}$$

High LAM indicates so-called stop-and-go behavior (e.g., traffic congestion); low LAM describes continuous movement without many halts. CRQA is a predictor of persistence in common states.

(6) Average vertical line length (Mean V) estimates the average time the system remains in a specific state:

$$\text{Mean V}=\frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=v_{min}}^{N} P(v)} \tag{7}$$

High Mean V indicates longer vertical lines or prolonged laminar states, i.e., less dynamic change. Low Mean V shows shorter vertical lines or rapid transitions between states. CRQA shows the duration of typical laminar phases.

(7) Maximum vertical line length (Max V):

$$\text{Max V}=\max v\text{, for all } v\geq v_{min} \tag{8}$$

High Max V indicates the longest period of laminarity or state persistence (i.e., the system stayed nearly unchanged for a prolonged time). Low Max V suggests short-lived states, frequent transitions, or instability. CRQA determines the longest continuous laminar phase.

(8) Trapping Time (TT) indicates the average time the system spends in one state:

$$TT=\frac{\sum_{v=v_{min}}^{N} vP(v)}{\sum_{v=v_{min}}^{N} P(v)} \tag{9}$$

High TT indicates the system remains trapped in the same state for longer periods (e.g., constant-speed cruising). Low TT means the system transitions quickly between states, reflecting more dynamic or unstable behavior. CRQA indicates the average duration of shared laminar phases.

2.3 Dataset

The dataset, containing inertial measurements from smartphones inside vehicles during driving, includes parameters like longitude, latitude, speed, distance, time, accelerometer (Acc_X, Acc_Y, Acc_Z, 14250 x 3 samples), and gyroscope (Gyro_X, Gyro_Y, Gyro_Z, 14250 x 3 samples) [11]. Data were collected under natural driving conditions on various road types, surfaces, and traffic environments, with multiple drivers contributing to individual driving styles. However, uncontrolled environmental factors and inter-driver variability pose limitations.

3 Problem Solution

The first step in our data analysis is to normalize our data to achieve a standardized data format.

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{10}$$

A recurrence threshold of 0.1 was chosen to maintain a recurrence rate (RR) between 2–5%, i.e., only 2–5% of all possible points in the RP are marked as recurrent.

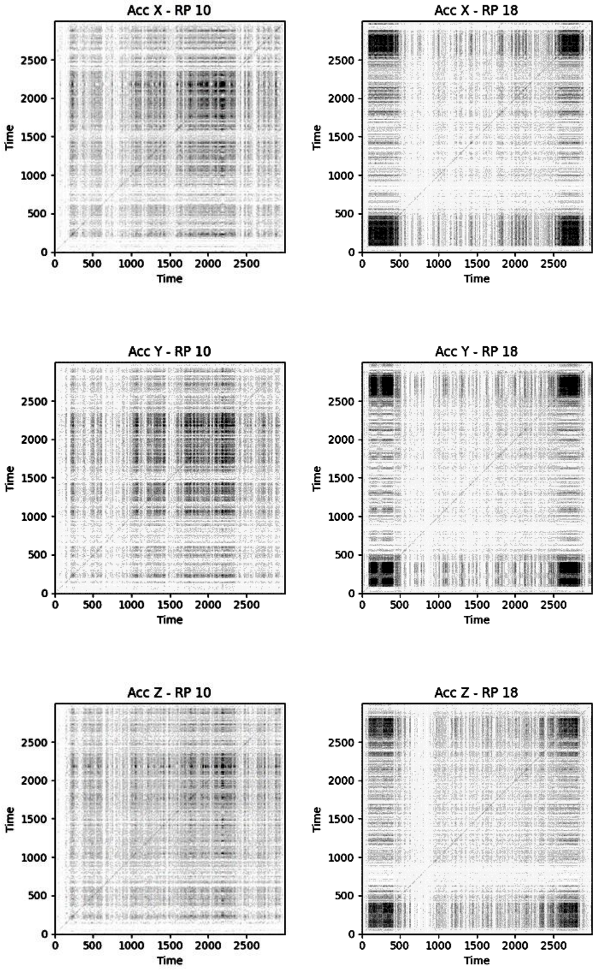

Fig. 2. Representative patterns of RPs from accelerometer time windows 10 and 18 are shown. Data were collected along the Ox, Oy, and Oz axes, revealing qualitatively distinct dynamics across the windows

This balance ensured sparsity and interpretability. A higher value of 0.2, however, resulted in crowded and difficult-to-interpret plots. Eight quantitative descriptors of the recurrence plot were computed. A sliding window method with a window length of 3000 samples and an overlap of 80% was used to generate an RP.

Figure 2 presents recurrence plots (RPs) that illustrate distinct motion patterns during two different driving moments, chosen based on a time-window approach. Plots for time window 10 appear fragmented and contain noisy areas, suggesting an unstable or inconsistent driving behaviour, possibly involving sudden accelerations or braking. Plots for time window 18 show a mixed pattern that combines structured and scattered regions. It may reflect transitions between smooth and dynamic driving phases, such as stop-and-go traffic or brief manoeuvres.

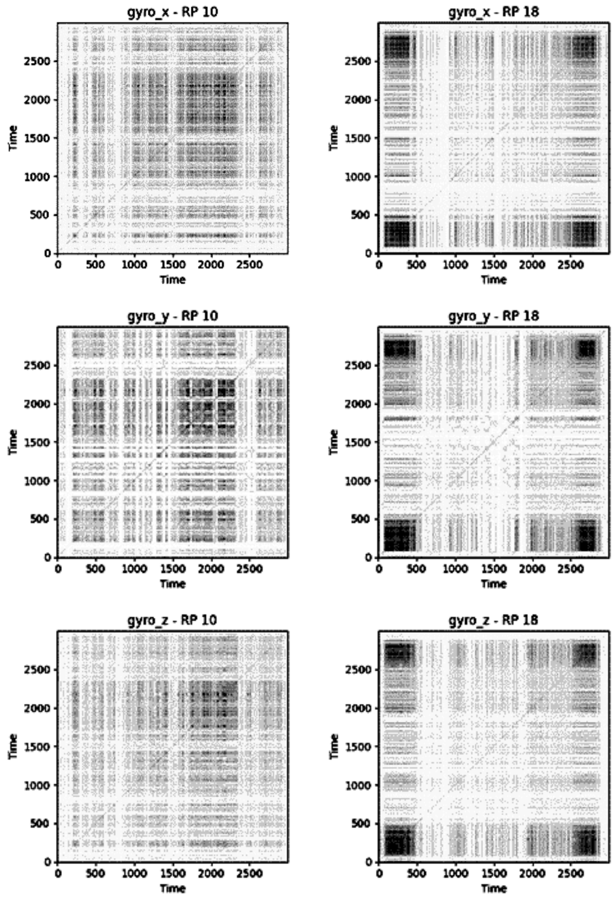

Fig. 3. Representative patterns of RPs from gyroscope time windows 10 and 18 are shown. Data were collected along the Ox, Oy, and Oz axes, revealing qualitatively distinct dynamics across the windows

Figure 3 depicts RPs computed from gyroscope signals. For the time window 10, broken and uneven structures exist, suggesting that control is unstable or that directions change suddenly. Time window 18 shows a mixed pattern with both structured and scattered areas. These suggest smooth transitions between dynamic driving phases, such as stop-and-go traffic. The textural patterns of RPs reveal variations across different driving moments. RPs are symmetric along the main diagonal, and the intensity of darkness represents the strength of recurrence. Dark squares indicate specific frequency bands, while the width of vertical bands reflects the duration or gradual change of a particular driving state. Horizontal bands signify repetitive behaviors, suggesting consistent or recurring driving patterns. In contrast, fragmented or noisy bands indicate irregular control, often associated with distraction, fatigue, or aggressive driving. This short-term, sliding-window analysis, aggregated across trips, enables long-term driver behavior profiling. To quantitatively assess the nonlinear system dynamics, the statistical properties of the analysed descriptors are presented in Fig. 4.

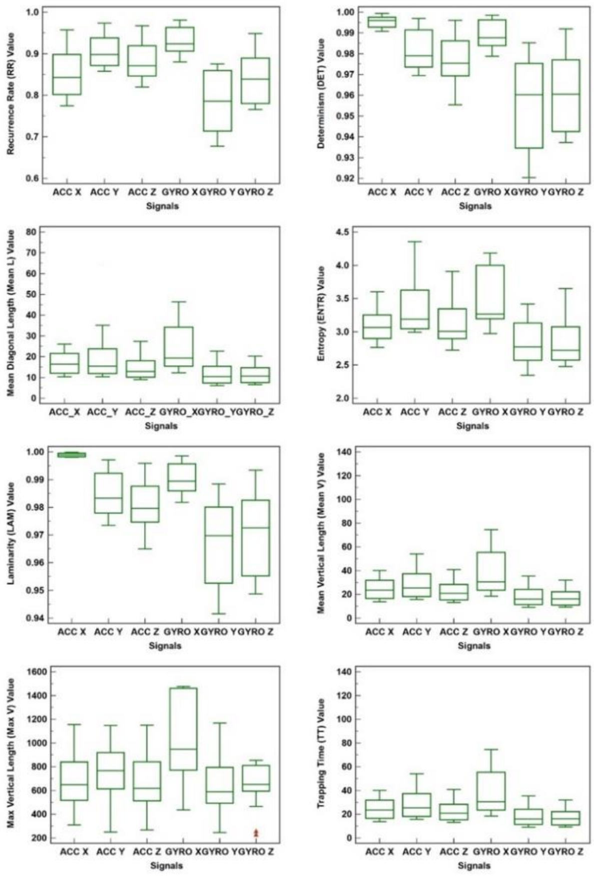

Fig. 4. Box and whisker plots for RQA parameters (RR, DET, Mean L, ENTR, LAM, Mean V, Max V, and TT) generated for 18 data scenarios based on a sliding window strategy. They illustrate the distribution and variance in acceleration and gyroscope data.

Univariate RQA translates RP patterns into numerical descriptors of system dynamics. On the X-axis, accelerometer data show a highly stable and repetitive signal, with minimal variation. The gyroscope component on this axis confirms extended periods of predictability. The LAM(Ox) metric approaches 1 across all windows, indicating exceptional laminarity and stability. The TT emphasizes the prevalence of frequent resting or slow-motion phases. Elevated DET values (≈1) underscore the pronounced repetitiveness of the signal. The long diagonal lines substantiate regularity, while high DET alone does not establish it. Low ENTR values corroborate these findings, indicating excellent predictability and minimal structural complexity. Conversely, Oy and Oz signals demonstrate increased unpredictability and disjointed dynamics, characterized by brief recurrence intervals and moderate stability. Low and dispersed LAMY, LAMZ signify unstable patterns characterized by frequent state transitions. MaxV highlights periods of stationarity. An anomaly in GYRO_Z (red triangle, Fig. 4) indicates an unusually extended rest state, probably resulting from prolonged idling, continuous linear motion, or sensor-related issues such as drift or alignment inaccuracies. The outlier does not necessarily indicate poor driving but rather an unusual situation where angular dynamics remain stable for an extended period. Minimal TT values for GYRO_Y and GYRO_Z confirm highly dynamic signals characterized by rapid transitions. Results of the CRQA on the 18 data scenarios using a sliding window strategy for acceleration and gyroscope data are shown in Table 1.

Table 1a. Overview of CRQA measures (Acceleration channels)

Indicator	ACC_X	ACC_Y	ACC_Z
RR	0.268805	0.308705	0.090334
DET	0.898583	0.649174	0.290609
Mean L	5.139301	6.132572	2.978915
L max	976	506	36
Divergence	0.001025	0.001976	0.027778
L_ENTR	2.118624	2.209653	1.362110
LAM	0.945834	0.761056	0.430141
TT	5.267134	6.746725	2.933520
Max V	1143	775	43
(V_ENTR)	2.072743	2.077256	1.289951
Mean V	12.70447	10.34677	18.364379
W_max	14178	13562	13989
W_div	0.000071	0.000074	0.000071
W_ENTR	2.920904	2.834308	3.447644
DET / RR	3.342876	2.102890	3.217040

LAM/DET	1.052584	1.172346	1.480133

Table 1b. Overview of CRQA measures (Gyroscope channels)

Indicator	Gyro_X	Gyro_Y	Gyro_Z
RR	0.967523	0.993445	0.999569
DET	0.986955	0.998461	0.999853
Mean L	67.823187	592.179242	2360.311703
L max	2027	8969	12935
Divergence	0.000493	0.000111	0.000077
L_ENTR	4.652126	6.063098	6.694672
LAM	0.992668	0.998893	0.999907
TT	90.705034	931.706713	3359.647807
Max V	2530	6347	12722
(V_ENTR)	4.227109	4.501136	4.026545
Mean V	5.332341	7.691173	4.246971
W_max	12115	1506	73
W_div	0.000083	0.000664	0.013699
W_ENTR	1.713352	2.471193	1.906374
DET / RR	1.020084	1.005049	1.000284
LAM/DET	1.005789	1.000433	1.000054

The experimental data shows that despite using the same threshold $\epsilon = 0.1$, the RR for the gyroscope data is extremely high. This means almost every point is counted as recurrent, indicating significant variability between the accelerometer and gyroscope signals. Therefore, it is recommended to use a different threshold value when analysing the gyroscope data. This will be the focus of a future study.
Table 1 reveals that accelerometer data display greater variability and irregularity, particularly along the Z-axis (vertical), reflecting frequent translational movements such as jolts and decelerations. In contrast, gyroscope signals exhibit consistent, repetitive, and stable patterns across all axes, indicating smooth and controlled rotational motion. TT, Max V, and DET/RR ratios highlight the contrast between the accelerometer's dynamic behavior and the gyroscope's steadiness. These results emphasize the value of recurrence-based analysis in capturing temporal dynamics and converting them into indicators, enabling precise characterization and classification of driving behaviors. Recurrence descriptors expose structured variability that conventional linear metrics often miss. CRQA reveals complex interdependencies among the driver, vehicle, and road, identifying coupling effects linked to specific driving contexts. There are some limitations, including the lack of data on road conditions (e.g., pavement quality, traffic), driver experience, and smartphone placement, which could introduce minor alignment inconsistencies. Despite these constraints, the recurrence-based and nonlinear dynamic framework proficiently detects organized variability in driving patterns that linear approaches fail to capture.

4 Conclusion

This study demonstrates that RQA and CRQA provide a thorough analysis of driver behavior through inertial sensor data. Recurrence analysis enables the identification of complex, nonlinear dynamic patterns within time-series signals. The results highlight the critical role of recurrence-based descriptors in capturing distinctive driving behaviors. Despite limitations related to dataset variability, the findings show that nonlinear dynamic analysis offers highly sensitive and discriminative metrics for assessing driver behavior.
Future research will focus on using different threshold values in RPs generation and integrating RQA features into predictive models for driver safety evaluation or adaptive vehicle control.

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