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Rider behavioral patterns in braking manoeuvres

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Abstract

This paper aims to investigate rider braking behaviors using a dataset of braking maneuvers derived from naturalistic riding data. Each braking event was fully characterized with experimental data. A set of descriptive parameters was defined to capture relevant information of the braking event and to facilitate the clustering process of braking behaviors. Naturalistic data of 5 riders were automatically processed to identify and characterize the braking events based on the given set of parameters. A preliminary descriptive analysis was performed to verify the presence of macro behaviors of riders. Subsequently, a Principal Component Analysis was performed to reduce problem dimensionality and support the cluster analysis on the dataset of a rider. The results indicated that a macro classification of riders is possible also based on a descriptive analysis. Nonetheless a cluster analysis sharply identified different behaviors of the rider, and thus provided a more solid basis for comparison of behavior among riders. In addition, the clusters revealed quantitative data that will be useful for the development of assistive systems.

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Keywords: Naturalistic riding; motorcycle; braking; rider behaviour; cluster analysis

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1. Introduction

1.1. State of the art

All riders are aware of the importance of braking maneuvers both in normal and safety critical conditions. Braking a Powered Two-Wheeler (PTW) brings together rider skills and technical characteristics of the vehicle, including its inherent instability. The complexity and importance of the braking maneuver has attracted the interest of scientists in the past decades, who have investigated this topic in order to optimize performances or to increase safety. In particular, Doria et al. (2000) optimized the parameters of the front suspension in order to minimize the stopping distance, while Cossalter et al. (2004) reproduced braking maneuvers under different road conditions, derived the correct braking style for each one and finally analyzed the implications for PTW stability. The topic of optimal maneuver was central also to several other papers, e.g., Cossalter et al. (1999), Limebeer et al. (2001), Hauser and Saccon (2006), Corno et al. (2008), Sharp (2009), and Sharp (2012). Beyond performance, braking is also the most frequent emergency maneuver according to in-depth crash data, MAIDS (1999) and Penumaka et al. (2014), and PTW accidents are still a relevant societal issue, IRTAD (2015). Braking in emergency conditions often leads to inappropriate maneuvers and occasionally to instability of PTW. Penumaka et al. (2014) observed both hard braking (i.e. close to wheel locking) and weak braking (i.e. sub-optimal braking) in accident data: the former being more common to experienced riders and the latter to novice riders. Several devices were developed to support riders during maneuvers, and also new systems are currently under development. To remove PTW front instability, Murakami et al. (2011) developed a front-steering assist control system to stabilize PTW during braking. Seiniger et al. (2012) performed a review of various assistive systems (e.g. Antilock Braking System –ABS–, Traction Control System –TCS–) and estimated the possible benefits of ABS on future accident data. More recently, a Motorcycle Autonomous Emergency Braking (MAEB) was proposed, Savino et al. (2012) and Giovannini et al. (2013), to support riders in the event of an unavoidable accident: the system integrated a mild autonomous braking, in case of a detection failure of the event by the rider, and an enhanced braking to maximize the deceleration, in case a voluntary braking action was detected. Its effectiveness was tested using accident reconstructions in Savino et al. (2013). In Symeonidis et al. (2012) the technical development of the system was complemented by a motion analysis, which concluded that the activation of autonomous braking with decelerations up to 0.35g did not induce additional instability compared to manual braking.

A limited number of papers focused on the human reactions related to braking. In Davoodi et al. (2011) the Perception-Response Time (PRT) of riders was experimentally determined in case of an expected braking event of a leading object. In Davoodi et al. (2012) a similar study was performed, always in controlled conditions, to determine the PRT of riders for expected and unexpected objects appearing on their path. In Dunn et al. (2012) a parametric experimental study was conducted to determine braking performance with different riders and braking strategies. Yuen et al. (2014) investigated the rider behavior while riding over a curve section in controlled conditions using an instrumented motorcycle.

Available literature shows that little attention was devoted to investigate rider behavior related to braking, while several works focused on technical solutions to improve braking. Nonetheless, the research in related sectors demonstrated the necessity to integrate riders' feedback in the development process of safety assistive devices, e.g. Diederichs et al. (2009). Thus this paper aims to fill the knowledge gap and provide an initial assessment of real-world rider behavior concerning braking using a naturalistic approach. The availability of such information, when appropriately generalized and extended, will be crucial to inform the design of new assistive technologies.

1.2. Study objectives

In this research, the possibility of a systematic analysis of rider behavior during braking maneuvers was investigated with the support of naturalistic data, i.e. riding data gathered with a fully instrumented PTW in normal riding conditions. To the authors' best knowledge, no previous research used this approach. This methodology for data collection is more likely to provide a dataset free from artifacts or any bias compared to observations in a test track or in controlled conditions. In addition it delivers a full experimental characterization of riders' braking actions with a single period of data acquisition.

The specific objectives of the study were the classification of riders according to a macro-behavior, and the identification of different braking strategies according to the desired braking performance.

2. Methodology

2.1. Data collection

Data were collected as part of the EU funded research project 2BESAFE (www.2besafe.eu) within a pilot study on naturalistic riding Baldanzini et al. (2010). The study, coordinated by the University of Florence (UNIFI), aimed to collect naturalistic riding data to investigate near-missed events and other dangerous riding conditions. Data collection was performed at four sites (located respectively in France, Greece, Italy and United Kingdom), and lasted 6 months in each site. Volunteer riders were recruited and were given an instrumented PTW to use in everyday life conditions. Each rider used the PTW for a period ranging from 1 up to 2 months. A common and minimal set of signals was agreed among partners, leaving each unit the possibility to integrate the minimal set with additional signals. Each team selected independently the most appropriate sensors to perform data acquisition, nonetheless minimal technical specifications had to be met in order to allow comparison of data among all sites. In addition, the sites shared a common recruitment procedure for riders defined through a set of procedures and document templates.

The common set of signals was comprised of: linear acceleration (three components); roll, yaw and pitch angles; longitudinal speed; brake activation; throttle position; steering angle; GPS position; turn signals; video: 2 cameras positioned to capture the frontal environment (required a minimum 90° field of view) and the rider's head. The UNIFI unit complemented the set of signals with roll, yaw and pitch rates, three components of velocity, wheel speed (front and rear), and brake pressures (front and rear circuits). Data collection was performed with a scooter (Piaggio Beverly Tourer 300ie). This choice reflected the fact that in the Florence area most of PTWs are scooters used for daily commuting. Data acquisition was performed in the period January to October. The scooter was not equipped with any brake assist device (e.g. ABS or Combined Braking System –CBS–).

Riders had not to perform any specific task related to the instrumentation secured in the top case and under the saddle. The whole instrumentation was powered as the scooter was started, and data acquisition started automatically. The riders were not asked to ride along specific routes or to perform any specific maneuver.

Collected data were processed and reduced in order to extract relevant events for the 2BESAFE project, Weare et al. (2011). However the full set of raw data (i.e. acquired data without any additional processing) was stored for further analyses. The raw dataset of UNIFI unit was used in the present study. Details of the riders are reported in Table 1.

2.2. Data processing

Raw data were processed to identify all braking events recorded during normal and safety relevant riding conditions. Specifically in this study the following signals were considered: longitudinal velocity; braking pressure of the front and rear circuits; longitudinal deceleration; yaw and roll rate; roll angle.

Velocity and acceleration data were filtered with a moving average, in order to eliminate environmental noise (i.e. caused from varying road conditions). After filtering, all data corresponding to a longitudinal speed lower than 0.55 m/s (2.0 km/h) were excluded from the event identification. In fact the threshold represents a quasi-static condition and thus is not of interest for investigating riding tasks. The automatic identification of braking events was integrated with a validation process, based on a set of minimal requirements (Table 2) to be simultaneously met in order to accept the braking event in the analysis. Braking events were characterized through the definition of a set of parameters, designed to extract the most relevant information of the braking action (Table 3).

The automatic event identification was eventually complemented with additional criteria in order to allow the joint processing of all braking events (i.e. combined braking and single circuit braking). In fact some of the parameters described in Table 3 were not defined in case of single circuit braking, and thus the assignment of a pre-defined value was necessary for an homogeneous processing of all braking events.

Table 1. Rider characteristics.

Subject	Gender	Age [years]	Riding experience [years]	Type of vehicle owned	Frequency of riding	Annual mileage [km]	Main motivation for riding
Rider 1	Male	28	12	Moped & motorcycle on/offroad	Daily	5,000	Commuting & leisure
Rider 2	Male	34	18	Moped & sport motorcycle	Daily	7,000	Commuting & leisure
Rider 3	Male	37	19	Scooter	Daily	2,000	Commuting
Rider 4	Male	29	7	Scooter	Daily	10,000	Commuting
Rider 5	Male	41	24	Scooter	Daily	10,000	Commuting

Table 2. Thresholds for automatic validation of braking events.

Signal	Threshold
Brake pressure	0.2 [bar]
Minimum pressure range within the braking event	1.5 [bar]
Duration of the braking event	0.4 [s]

Table 3. Description of parameters used to characterize the braking event.

Parameter	N. of variables	Description
Type of braking event	1	Identifies the type of braking action: only front or rear braking; combined braking.
Relative position of braking action	1	Applies to combined braking events. It analyses the sequence of activation of the front and rear circuits discriminating between the following different actions: a) action starts with rear or front braking only and ends respectively with front or rear braking only (intersected braking events); b) action starts and ends with rear braking only (front in rear braking); c) action starts and ends with front braking only (rear in front braking).
Duration	3	Overall braking event duration, and duration for each of the front and rear circuits.
Braking pattern	2	Shape of the braking action (respectively for the front and rear circuit): single, double or multiple peaks.
Start shift	1	Time shift of the pressure onset between the front and rear circuit (positive in case the braking action starts with the front circuit).
Maximum pressure	3	Maximum pressure value in each circuit and their sum.
Position of maximum pressure	2	Position in time of the maximum pressure in each circuit. The position is expressed as a percentage of the overall duration of the event (100% corresponds to the end of the event).
Shift of the maxima	1	Time shift between the maximum pressure of the front and rear circuit.
Velocity	3	Longitudinal velocity at the start and at the end of the braking event, and their difference.
Deceleration	2	Maximum deceleration and mean deceleration within the event.
Position of max. deceleration	1	Position in time of the maximum deceleration, expressed as a percentage of the overall duration of the event (100% corresponds to the end of the event).
Pressures at max. deceleration	2	Pressures in the front and rear circuits corresponding to the maximum deceleration.
Yaw rate	4	Yaw rate at the beginning of the braking event and at maximum deceleration, and their absolute values.
Roll rate	4	Roll rate at the beginning of the braking event and at maximum deceleration, and their absolute values.
Roll angle	3	Roll angle at the beginning of the braking event, at maximum deceleration and their difference.
Steering at max. deceleration	1	Steering position corresponding to the maximum deceleration.
Throttle	2	Throttle position at the start and at the end of the braking event.

2.3. Clustering

Each event was finally characterized by 36 parameters. The problem dimensionality could hamper the clustering process, thus a Principal Component Analysis (PCA) was performed prior to clustering. This technique is widely used to reduce the number of the dependent variables, e.g. Crundall et al. (2008) and Long et al. (2009). The number of components was defined by the criterion of explaining at least 80% of the total variance. Kaiser-Meyer-Olkin measure of sampling adequacy test and Bartlett's test of sphericity were run to assure the appropriateness of the factor analysis.

The rotated components obtained from the PCA were used to implement the clustering process. Two clustering algorithms were used to test the stability of the process: Two-step and K-means. Since in preliminary tests on the dataset of braking events, clusters with similar features and dimensions were obtained with the two algorithms, the final analysis presented in this paper was performed with the Two-step algorithm developed by Chiu et al. (2001). Further testing was performed on the dataset in order to verify the stability of the clusters, and the capability to discriminate among different rider behaviors. The results are presented in section 3.3.

3. Results

Naturalistic data of 5 riders were processed according to the method presented in the previous section. Datasets of different sizes were obtained according to different mileage and usage: 2603, 3039, 1321, 3028 and 1570 braking events were respectively extracted for rider 1 to 5. Since during acquisition, one or more sensors occasionally failed, not all signals were always available and thus a share of events could not be completely characterized according to the specified set of parameters (ref. section 2.2). During this first analysis of the dataset, focus was restricted to the fully characterized events and thus the datasets reduced to 177, 1183, 96, 1631, and 486 for rider 1 to 5 respectively (3573 braking events in total).

3.1. Descriptive analysis

Prior to a cluster analysis, a macro analysis of the datasets was performed to check the presence of different braking styles. *Type of braking event* and *relative position of braking action* were candidate parameters for the investigation. A Pearson Chi square test versus *riders* confirmed their significance as descriptive parameters (p<0.001). Detailed figures of the analysis are reported in Table 4. All riders performed predominantly combined braking maneuvers. Nonetheless it was possible to distinguish between the behavior of riders 1 and 3 (with respectively 87.0% and 83.3% of combined braking), and the behavior of the remaining riders (in the range 68.4% to 73.7%).

A breakdown of combined braking data confirmed a similar behavior within the group of rider 2, 4 and 5 showing lower proportion of combined braking: for all of them the combined maneuvers initiated and ended with the rear brake in the majority of the braking events (61.2% to 79.8%), while the front brake was typically used for a shorter time (‘*front in rear’* braking). In addition, this group was characterized by the highest share of *rear only* braking events (22.8% to 28.9% vs 4.0% to 4.2%).

The other group of riders (rider 1 and 3), besides having the highest share of combined braking, was characterized also by a higher frequency of *front only* braking events (9.0% to 12.5% vs 0.3% to 3.5% of riders 2, 4 and 5). An in-depth analysis of their combined braking strategy highlighted some differences: while rider 1 performed mostly ‘*intersected*’ braking (44.8%, i.e. braking initiated with a circuit and ended with the other one) and secondly a ‘*rear in front*’ braking (38.3%, i.e. braking initiated and ended with front brake and shorter rear brake usage), rider 3 performed mostly ‘*rear in front*’ braking (61.3%) and secondly ‘*intersected*’ braking (27.5%).

The analysis was extended to include the *braking pattern* parameter, which took into account the shape of the pressure signal during each braking event: discrimination was done among single, double, or multiple peaks. Front and rear braking actions were considered separately, without any distinction between single circuit or combined braking. Front brake data showed that rider 1 mostly modulated the use of the front brake (50.6%), while rider 3 mostly did not (54.3% single peak events). No statements can be made for the remaining riders. Differently, rear brake data demonstrated that riders 2, 3 and 5 preferentially did not use modulation (44.7% to 47.6% single peak events), while rider 4 mostly modulated rear brake pressure (53.9% multi-peak events, i.e. three or more peaks). Rider 1 used almost evenly no modulation and multiple peak modulation for rear brake.

Table 4. Distribution per rider of: braking type (*Type: front, rear, combined*), relative position of braking action (*Position: rear in front, front in rear, rear and front intersected*) and braking pattern (*Shape Front/Rear Brake: single, double, multiple peaks*) [%].

	Type			Position			Shape Front Brake			Shape Rear Brake		
Rider	Front	Rear	Comb.	Rear in Front	Front in Rear	R & F Inters.	Single Peak	Double Peak	Multi Peak	Single Peak	Double Peak	Multi Peak
1	9.0	4.0	87.0	38.3	16.9	44.8	33.5	15.9	50.6	38.5	21.7	39.8
2	0.3	28.9	70.8	5.1	79.8	15.1	34.5	25.3	40.2	44.7	25.4	29.9
3	12.5	4.2	83.3	61.3	11.2	27.5	54.3	14.2	31.5	47.6	26.2	26.2
4	2.7	28.9	68.4	8.8	65.4	25.8	36.6	21.5	41.9	23.9	22.2	53.9
5	3.5	22.8	73.7	10.0	61.2	28.8	42.7	27.4	29.9	46.5	21.7	31.8

3.2. PCA

The PCA was performed on the dataset of rider 4, using the 32 non-categorical parameters. As stated in section 2.3, the authors decided to select all the components that could explain at least 80% of the total variance. The analysis identified 10 components that explained 80.9% of the variance from the original variables.

3.3. Cluster description

Cluster analysis was applied to the dataset of rider 4. Two-step clustering was employed increasing from 3 to 5 the number of expected clusters, in order to check the stability of the results. The range in the number of clusters from 3 to 5 was selected based on the Schwarz Bayesian Criterion (BIC) and the change in BIC between adjacent number of clusters. After each processing, clusters were screened in order to verify if they were meaningful for behavior identification. As the number of cluster increased, two clusters slightly varied their dimension, but they were not modified in terms of identified behavior; differently the largest cluster was increasingly divided into new clusters (Table 5). Results showed that with 5 clusters it was possible to identify also a very specific and scarcely represented behavior of the rider (Tables 5 and 6).

Table 5. Distribution of events per cluster as a function of number of processed clusters

	Cluster number in final analysis				
# of processed clusters	1	2	3	4	5
3	22%	18%		60%	
4	22%	16%	39%	23%	
5	22%	16%	37%	22%	3%

Each cluster was distinctively characterized through the variables defined in Table 3. Relevant features are reported in Table 6. Clusters effectively represent different sets of maneuvers:

- cluster 1: groups short and light braking events (figure 1a), as we could observe in typical heavy traffic situations, with low maximum deceleration (figure 2a), and coupled with throttle usage;
- cluster 2: groups braking events where the action started with non-zero roll (tilted vehicle), typically ending with the scooter in upright position (figure 1b). Combined braking or just rear braking was applied, typically involving average braking intensity (figure 1a). The resulting deceleration was scattered over a wide range of values (figure 2b);

- cluster 3: represents what appeared as “planned” braking maneuvers, performed with similar intensity of cluster 2 (figure 1a), but with the motorcycle already in a near-to-upright position, and no relevant lateral maneuver was applied by the rider (figure 1b). The cluster showed a reduced scatter in the deceleration, which was constant over a wide range of initial velocities (figure 2c);
- cluster 4: includes “hard braking” maneuvers, although still in normal riding conditions. These events were both characterized by higher braking pressures (figure 1a) and maximum deceleration mostly above $2m/s^2$ (figure 2d).
- cluster 5: includes all front braking events with light braking pressure (figure 1a) and mild deceleration (figure 2e), independently from the initial speed. This braking action can be classified as “velocity correction at high speed”.

Table 6. Cluster main features (quantitative data represent the mean value of the cluster).

Cluster number	%	Description
1	22	Rear only braking events; low braking intensity (maximum pressure: 5.9bar); low median initial velocity (39.3km/h); lowest deceleration; short braking (duration 2.2s); no clear pattern for brake modulation.
2	16	Rear only, and combined braking events (in this case mainly *front in rear* braking); average braking intensity (sum of maximum pressures: 12.8bar); low initial velocity (37.7km/h); maximum roll rate among all clusters at maximum deceleration; maximum variation of the roll angle between the start of the maneuver and the maximum deceleration; throttle activated both at the start and end of the braking event (highest median value for the throttle angle at the end of braking event among all clusters); average event duration (duration 3.4s).
3	37	Only combined braking events (mainly *front in rear* braking); average braking intensity (sum of maximum pressures: 14.3bar); high initial velocity (47.5km/h); braking in near-to-upright position and no maneuver while braking; throttle not active; average event duration (duration 3.6s).
4	22	Only combined braking events (mainly *front in rear* braking); highest braking intensity (sum of maximum pressures: 25.5bar); this cluster also include the majority of brake-to-halt events; high initial velocity (52.9km/h); braking in near-to-upright position and no maneuver while braking; throttle not active at onset of braking; same throttle value at the onset and end of events, but 3rd and 4th quartile of throttle angle at end show acceleration in some events; highest deceleration and longest event duration (duration 7.1s) among all the clusters; maximum deceleration reached mostly in the second half of the braking event (57%); braking modulation of the front and rear brakes (almost all events with more than 2 peaks).
5	3	Front only braking events; lowest braking intensity (maximum pressure: 4.2bar); highest initial and final velocity (respectively 53.7 and 50.0km/h); braking in near-to-upright position and no maneuver while braking; throttle not active; shortest braking action (duration 1.1s); mostly no modulation of braking (i.e. 1 peak).

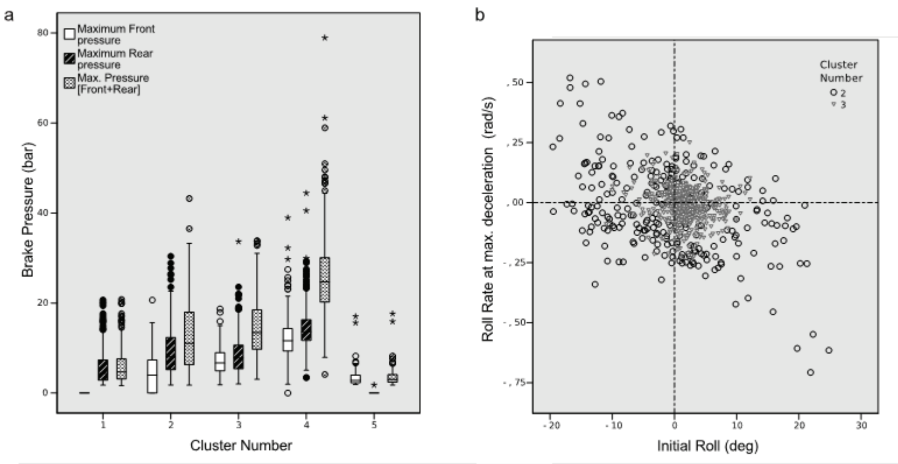

Fig. 1 (a) Box-plot of maximum rear and front pressure, and their sum for each cluster (o – outlier value; * - extreme value); (b) Roll rate at maximum deceleration versus initial roll angle for clusters 2 and 3.

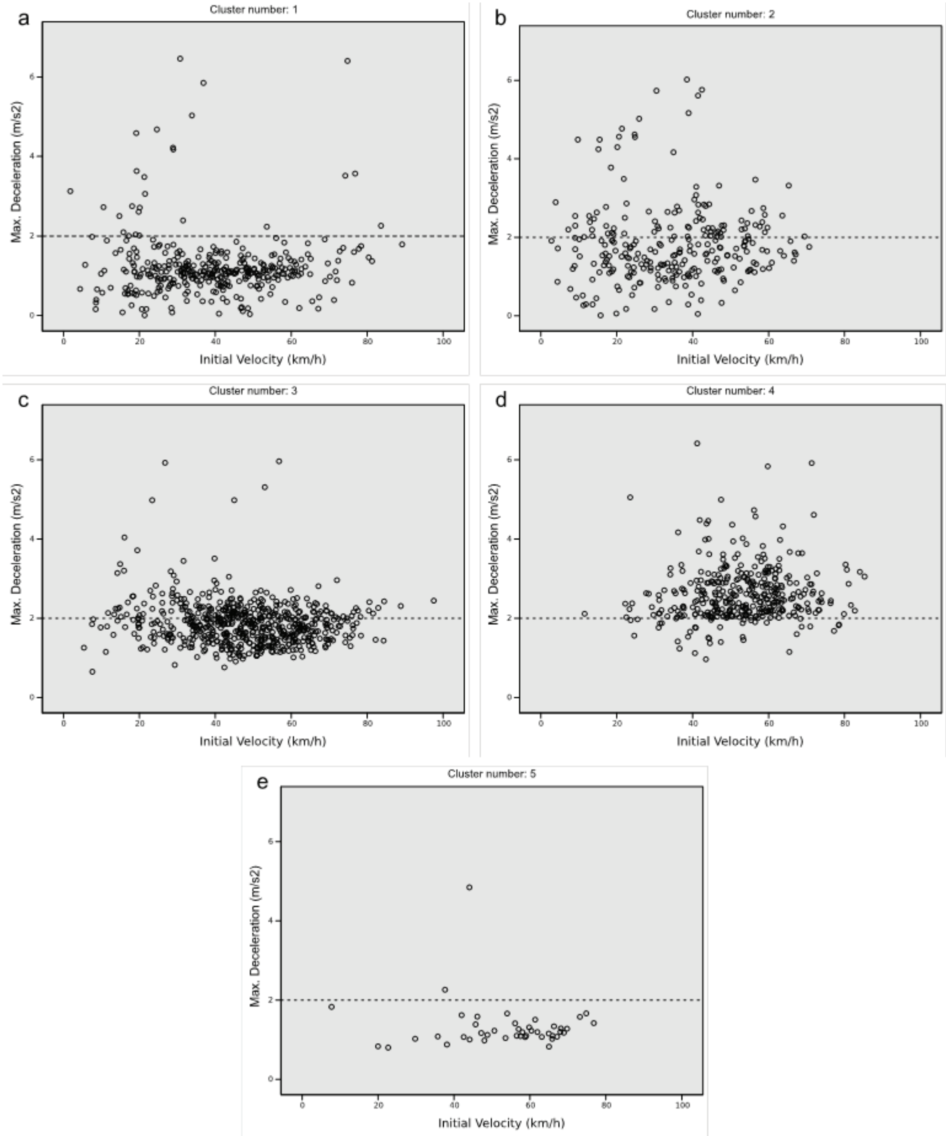

Fig. 2. Scattered distribution of maximum deceleration vs initial velocity of the brake events for (a) cluster 1; (b) cluster 2; (c) cluster 3; (d) cluster 4; (e) cluster 5.

4. Discussion

The results of the cluster analysis confirmed that the set of parameters identified for the characterization of the braking events was capable to capture the relevant information within the event. In fact the cluster algorithm successfully identified 5 clusters with different braking maneuvers.

Only one cluster had braking with tilted motorcycle at the beginning of the event. This cluster was highly identifiable since its definition and size was stable throughout the different cluster analyses with increasing number of clusters. The data showed that the highest roll rates occurred during maneuvers in which the motorcycle returned to an upright configuration, while increase of roll angle was associated to low roll rates (figure 1b). Also the cluster of braking events involving only the rear brake was always present in the cluster analyses. In future works the presence and relevance of such clusters should be verified also for other riders.

The other clusters, which did not involve roll parameters, gave relevant information about the deceleration adopted by the rider. Figure 2 shows that a $2m/s^2$ deceleration was a discriminant for normal to hard braking, and that the implemented deceleration was not a function of the initial velocity. In fact, clusters 1 and 2 had respectively a mean deceleration of 1.8 m/s^2 and $1.9m/s^2$, while cluster 4 and 5 of 1.3 m/s^2 and $1.2m/s^2$: only in cluster 3, labeled as “hard braking”, the majority of events had a deceleration above $2m/s^2$ (mean value $2.6m/s^2$). In the future, the analysis of the other datasets will add information about the threshold for deceleration, showing whether a threshold exists also for other riders.

5. Conclusions

In this paper a framework for the analysis of riders’ braking behavior using naturalistic data was presented. The methodology comprised the identification of a set of parameters, capable to extract relevant information from the braking events, followed by a Principal Component Analysis and a clustering process. The signals, gathered during the naturalistic riding study of the 2BESAFE project, were processed to perform an automatic braking event identification and calculation of the parameters. A preliminary descriptive analysis, based only on a subset of the defined parameters, was performed on the data of 5 riders. The results demonstrated the existence of clear distinctive behaviors that were common to this group of riders. In particular, 3 riders with a predominant usage of rear brake (alone or in a combined braking scheme) were identified; the 2 remaining riders were seen to use more combined braking (either with front and rear brake on the same level or with a preference for front brake) and also only front braking. Clustering was then applied to the dataset of one rider with a predominant usage of rear brake. Five clusters corresponding to relevant behaviors were identified: braking with non-zero roll, normal braking, hard braking, light braking at high speed, and mild braking coupled with throttle usage. The clusters were rich of information and allowed to identify a threshold value of deceleration, which discriminated between normal/mild and hard braking events.

The results proved the effectiveness of the method and the relevance of naturalistic data to investigate riders’ braking. The in-depth knowledge of rider behaviors, that the proposed approach enabled, opens new perspectives for the design and assessment of advanced safety technologies. In particular, since their initial stages of development new assistance systems may take account of a new set of detailed user characteristics retrieved in the real world. For example, the study finding that high roll rates during braking were mainly seen when the rider was maneuvering the PTW to upright position, rather than vice-versa, can identify relevant case studies for the development of braking assistance systems such as autonomous emergency braking. However, an extension of the analysis is required to derive more robust data, and also to answer to new research questions arisen during this work.

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