Action pattern recognition based on Action phases clustering

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Short summary

Current approaches to identifying driving heterogeneity often struggle with accurately deciphering fundamental patterns inherent in driving behaviour. The concept of *Action phase* is proposed to capture underlying driving characteristics with physical meanings. This study further recognises *Action patterns* by clustering extracted *Action phases*. A Resampling and Downsampling Method (RDM) is first applied to standardise *Action phases* length. Using features selected by Principal Component Analysis (PCA), two clustering algorithms, i.e., Agglomerative clustering with dynamic tree cut and X-means clustering, are utilised to group *Action phases* with high similarity. Six *Action patterns* named "Catch up", "Fall behind", "Follow behind", "Speed up", "Slow down", and "Hold speed" are finally recognised based on clustering results. Further statistical analyses demonstrate that velocity and time headway exhibit higher importance than other variables in characterising driving behaviour. The methodology and findings presented in this study offer a nuanced approach to interpreting driving behaviours, which can help to enhance the accuracy of driving heterogeneity identification.
Keywords: Driving heterogeneity; Action pattern recognition; Action phase; Clustering.

1 Introduction

Driving heterogeneity, recognised as the differences in driving behaviours exhibited by different driver/vehicle combinations under similar conditions, is widely acknowledged (Ossen et al., 2006). Studies have shown that heterogeneity in driving behaviour can lead to a rise in traffic accidents, congestion, and emissions (Sun et al., 2021; Kerner & Klenov, 2004). Further, user acceptance of autonomous vehicles (AVs) has been found to depend on accurately comprehending and emulating driving heterogeneity of human-driven vehicles (HDVs), such as human drivers' preferred driving styles (Tavakoli & Heydarian, 2022). Thus, understanding driving heterogeneity significantly enhances traffic operations and enables manufacturers to design safe and efficient automated vehicles at various levels.

Existing studies have addressed driving heterogeneity by personalising driving styles based on driving behaviour data such as vehicle kinematics variables (e.g., velocity and headway) and vehicle dynamics variables (e.g., braking and throttle opening), which enable categorising drivers into several groups (Zou et al., 2022). For instance, W. Wang et al. (2017) classified drivers into two categories (i.e., normal, and aggressive) based on velocity and throttle opening data. In another study, overtaking manoeuvres were identified as low-medium-high risk levels based on speed and distance between vehicles (Figueira & Larocca, 2020). Other studies have utilised car-following model parameters to distinguish driving styles (Sun et al., 2021). These methods capture drivers' static driving characteristics, while not capable of describing the inherent traits of driving behaviour. This is because driving behaviour is a dynamic decision-making process (Zou et al., 2022), and drivers may exhibit heterogeneous driving styles in different traffic scenarios. Even under the same traffic scenario, the same driver's behaviours might vary at different time intervals. These have underscored the necessity of capturing driving heterogeneity from the underlying mechanism of driving behaviour.

Studies have found that driving heterogeneity can be derived by decomposing driving behaviour into distinct primitive patterns. Driving behaviour displays certain characteristics during the transition of driving manoeuvres (Terada et al., 2010). As such, some researchers segmented driving behaviour data into *primitives* with unique characteristics (Bender et al., 2015; H. Liu et al., 2014). By doing so, the characteristics of driving behaviour can be accurately captured by corresponding the traffic environment and driving manoeuvres. Using supervised learning approaches, different patterns were extracted and assigned with semantic labels (e.g., rapidly closing in, falling behind) by learning sample features like vehicle operating data (Zou et al., 2022). However, pre-labelling tasks are labour-intensive, limiting the implementation of supervised learning technologies in driving pattern recognition (Ackerman, 2017). As a result, there is a growing interest in semantic analysis using unsupervised techniques. Higgs & Abbas (2014) identified a specific set of state-action clusters and employed them to characterise potential driving patterns of passenger car and truck drivers. Employing a hierarchical Dirichlet process-Hidden semi-Markov Model (HDP-HSMM), W. Wang et al. (2018) extracted 75 primitive driving patterns from time series driving data. This method allows for the identification of a wider variability in driving behaviour by encompassing different driving characteristics. However, an excessive number of patterns, for example, 75, may limit the categorization's effectiveness due to reduced interpretability. This expansive classification has limitations in fully clarifying fundamental driving behaviours and understanding driving heterogeneity. As a result, continued efforts are required to overcome these challenges.

In our previous research (Yao et al., 2023), the concept of *Action phases* was introduced to capture driving characteristics with physical meanings, thereby facilitating the identification of driving heterogeneity. An *Action phase* is defined as a distinct segment of driving behaviour, where each phase is characterised by specific, observable actions or changes in driving variables. These phases are labelled according to the *action trend* exhibited by each variable within that phase. The *action trend* space for each driving behaviour variable is represented as $S = \{I, D, H, L\}$, which denotes 'Increasing', 'Decreasing', 'keep in a high value', and 'keep in a low value' of variables, respectively. Four variables named velocity (v), acceleration (a), time headway (T), and speed difference (Δv) are considered. Each *Action phase* is uniquely identified by a label name, where every variable within the phase adheres to a single *action trend.* Consequently, the collection of all the *Action phases* extracted from a certain dataset forms the *Action phases* Library for that dataset, representing the complete range of driving behaviour characteristics under specific traffic flow conditions. This concept expands the scope of the "action point" (Knoop & Hoogendoorn, 2015) by incorporating additional variables to provide more comprehensive information about driving behaviour. However, the introduction of additional variables can complicate the interpretation of driving behaviour. An increase in the number of label names leads to more distinct *Action phases*, which extends *Action phases* Library with many *Action phases* differing only slightly in their representation of driving behaviour. As such, consolidating *Action phase* with similar characteristics into a smaller number of patterns can assist in interpreting driving behaviour through the analysis of group-specific characteristics.

To bridge these research gaps, this study presents a method to classify *Action phases* into various *Action patterns*, paving the way to identify driving heterogeneity. The unique contributions of this study include: (i) The method applies *Action phases* with physical meanings in an unsupervised learning framework, which holds dual advantages in eliminating pre-defined bias and ensuring behaviourally interpretable results, and (ii) The proposed clustering calibration process assists in assessing variable importance and deriving *Action patterns* with interpretable semantic meanings. Evaluation using real-world datasets demonstrates various *Action patterns* with unique characteristics, reflecting empirically observed driving behaviours. The findings demonstrate the prospective advantages of using *Action patterns* to illustrate heterogeneity in driving behaviour.

2 Methodology

In this section, we introduce the methodology of *Action pattern* recognition, including an overview of the recognition process and techniques employed in each step.

Action pattern recognition aims to categorise all *Action phases* in *Action phase* Library into several groups which can be interpreted with semantic meanings. The results can be used in driving behaviour analysis such as guiding the labelling process of driving heterogeneity based on supervised machine learning methods. The process of *Action phases* extraction is outlined as the first part in Figure 1, which details can be found in our previous work (Yao et al., 2023). Using extracted *Action phases*, unsupervised learning methods are utilised to cluster similar *Action phases* and distinguish different groups, and *Aciton patterns* are recognised by analysing these clusters.

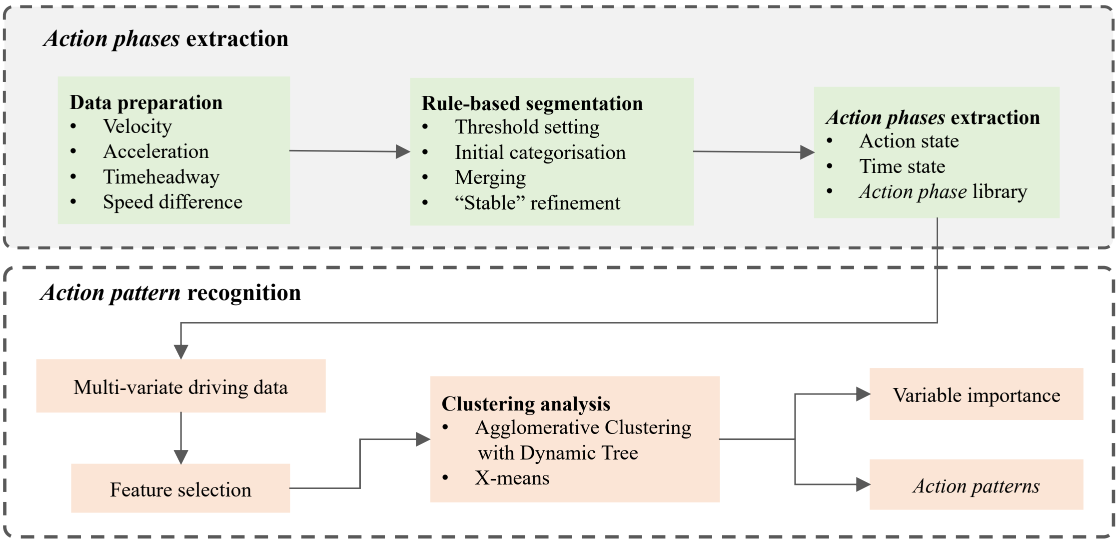


Figure 1: An overview of the process for *Action pattern* recognition.

Note that *Action phases* accommodate driving trajectory segments with varying lengths to provide a more detailed representation of driving behaviour characteristics, thus adding complexity to time-series analyses as most algorithms necessitate input data of equal length. To standardise the length of input data while preserving the information of the original *Action phases* to a large extent, the Resampling and Downsampling Method (RDM) is utilised. Simply, *Action phases* shorter than a referred length, i.e., median length, are resampled using Fast Fourier Transform (FFT) and Inverse Fourier Transform (IFFT) (Q. Liu et al., 1998) and those exceed the referred length are downsampled using isometric extraction. Since the extracted *Action phases* are multi-variable time-series driving trajectory data, feature selection is conducted to avoid limitations of high-dimensional data redundancy (Sun et al., 2021). The extracted features serve as input for the subsequent clustering analysis with an unknown cluster number k.

In the field of data clustering, various clustering approaches have been proposed, each with inherent techniques. According to Fraley & Raftery (1998), these clustering approaches are generally divided into two categories: hierarchical and partitioning techniques. In this study, We utilise Agglomerative clustering with dynamic tree cut and X-means, representing hierarchical and partitioning methods, respectively. Agglomerative clustering can detect clusters within clusters and adapt to the varying densities and shapes of the data clusters, which is particularly useful for *Action phases* data that cluster sizes may vary significantly. Specifically, it follows a bottom-up approach, which starts by considering each data point as a single cluster and then progressively merges the most similar cluster pairs (Ackerman, 2017). The process continues until a single cluster is formed or a predetermined stopping criterion is reached. The dynamic tree-cut method further refines this process by analysing dendrogram structures to make context-sensitive decisions on where clusters should be divided. In contrast, X-means clustering, an extension of the K-means algorithm, offers a flexible approach to determining the optimal number of clusters. Rather than requiring a predefined number of clusters, X-means starts with a lower bound for k and iteratively adjusts it, trying to find the best number of clusters according to selection criterion such as the Bayesian Information Criterion (BIC) (Pelleg & Moore, 2000). This method maintains a level of scalability and efficiency similar to K-means while mitigating the dependency of pre-defined cluster numbers. The integration of the aforementioned two clustering methods can facilitate a more nuanced and accurate categorisation of *Action phases* and recognition of *Action patterns*.

3 Experiments

Data preparation including *Action phases* extraction and feature selection is first introduced in this section. Then, experimental settings of clustering are provided.

As proposed by Yao et al. (2023), driving behaviour trajectories are segmented to yield *Action phases*, with each driving variable in these phases displaying a single trend. For example,

(D, L, L, I) indicates the vehicle's velocity (v) has a trend of decreasing, the acceleration (a) and time headway (T) are keeping a low value, and the speed difference (Δv) is increasing. All the *Action phases* extracted from one dataset (representing a specific traffic flow condition) constitute the *Action phase* Library of this dataset, which is adopted as the initial data in this study. We adopted 2800 vehicles from the Lyft5 dataset in this study, and the size of the *Action phase* Library amounts to 18800.

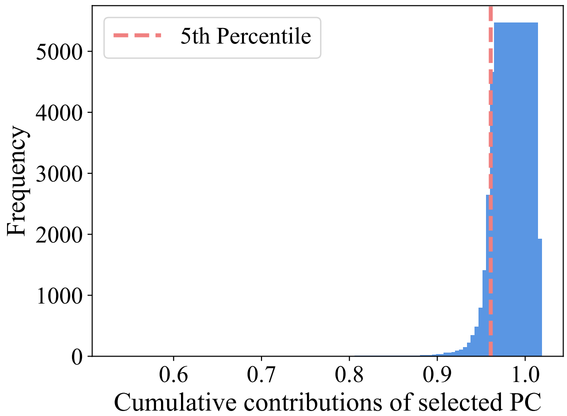


Figure 2: Distribution of PC1's cumulative contributions.

This study employs a widely-used unsupervised feature selection method, Principal Component Analysis (PCA), to cohere variables and extract significant features. As the results displayed in Figure 2, the cumulative contribution of the first Principal Component (PC1) exceeds 95% for 96.08% of *Action phases*, as indicated by the red dotted line in shows. Consequently, PC1s are selected and used as the input for subsequent clustering analysis.

For X-means clustering, the similarity between clusters is measured using a widely-used metric, i.e., Euclidean distance, and the cluster k ranges from 4 to 7. For agglomerative clustering, results are evaluated by examining different (intermediate) clusters, i.e., branches. The final clusters are determined by a linkage function with certain thresholds. There are several linkage functions, each with its specific focus. For example, the Weighted Pair Group Method with Arithmetic Mean (WPGMA) algorithm computes the distance between two clusters based on the average pairwise distances in the original clusters. And, Ward's method aims to minimise the variance within clusters (Murtagh & Contreras, 2012). We employed commonly used linkage functions including 'weighted', 'average', 'complete', and 'ward' in our clustering calibration process. Both agglomerative clustering and X-means are evaluated by three commonly used indexes: Silhouette Score (SS), Calinski-Harabasz Index (CHI), and Davies-Bouldin Index (DBI) (X. Wang & Xu, 2019). Specifically, the Silhouette Score is calculated using $(b - a)/max(a, b)$, where a and b represent the mean intra-cluster distance and the mean nearest-cluster distance for each sample, respectively. The best value is 1 and the worst value is -1. CHI score is higher when clusters are dense and well separated. For the DBI score, values closer to 0 represent better clustering performance.

4 Results and discussions

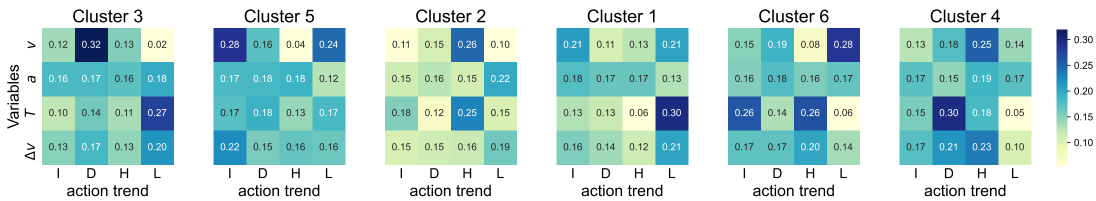
This section presents the results of *Action pattern* recognition, in which variable importance is evaluated as well.

Table 1 shows the results of Agglomerative clustering with different linkage functions and X-means clustering with different k values. As the bold text highlighted, Agglomerative clustering with a 'ward' linkage function and X-means with an $k = 6$ outperform their counterparts, respectively. Both of the optimal methods indicate six clusters, recognising six *Action patterns*. All *action trends* in each cluster are counted and visualised, as shown in Figure 3. Gradients of colour represent the percentage frequency of each *action trend* in different clusters. Note that frequency

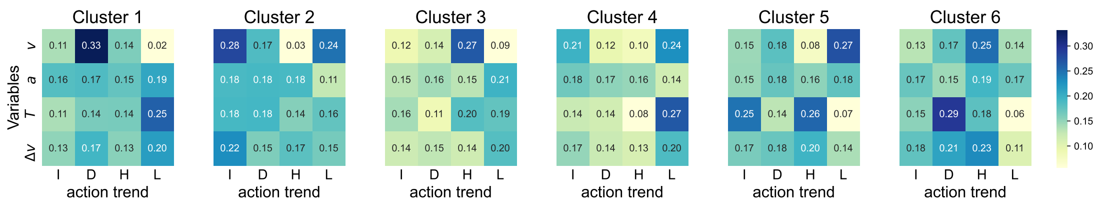
Table 1: Results of agglomerative and X-means clustering.

	linkage	SS	CHS	DBS	Clusters
Agglomerative clustering	average	0.37	4229.43	**0.72**	8
	complete	0.28	6286.08	0.90	8
	weighted	0.31	5823.54	0.92	7
	ward	**0.41**	**14673.48**	0.83	**6**
X-means	/	0.44	14115.50	0.81	4
	/	0.45	14638.43	**0.79**	5
	/	**0.46**	**15768.43**	0.80	**6**
	/	0.38	14740.08	0.00	7

characteristics of *action trends* can correspond to each other between two clustering methods. For example, Cluster 3 of Agglomerative clustering has similar colour gradients with Cluster 1 of X-means clustering. Furthermore, the frequency statistics of *Action phases* in each cluster also show the corresponding similar size between the two clustering methods, as presented in Table 2. This consistency in pattern and size of clustering results illustrates the underlying six patterns of *Action phases*. According to Table 1, X-means shows better clustering results than the Agglomeration method, thus we adopt X-means results to conduct further analyses.



(a) Agglomerative Clustering with Dynamic Tree



(b) X-means

Figure 3: Statistics of *action trends* in each cluster.

Table 2: Statistics of *Action patterns*.

Method	Clusters and the corresponding size					
Agglomerative clustering	1	6	3	5	4	2
	3301	3474	4124	1877	480	5544
X-means	4	5	1	2	6	3
	3025	3299	3902	2603	474	5497

In each cluster, *action trends* with high percentages are regarded as main variables and used to interpret driving behaviour and recognise *Action patterns*. For example, in Cluster 1, velocity (v) and time headway (T) are main variables with *action trends* of 'D' and 'L', indicating that velocity is decreasing and time headway is keeping. Thus, this cluster can be interpreted as a "Slow down" pattern. Similarly, in cluster 6, time headway decreases and velocity keeps, indicating that the following vehicle is closing its preceding vehicle, thus labelled as a "Catch up" pattern. In this way, six *Action patterns* are recognised according to their observations, as demonstrated in Table 3.

Table 3: *Action pattern* interpretation.

Clusters	**Main variables**	**action trend**	**Observations**	**Action patterns**
1	v, T	D, L	Speed decreasing, time headway keeping	Slow down
2	v, Δv	I, I	Speed increasing, speed difference increasing	Speed up
3	v, T, a	H, H, L	Speed keeping, small acceleration	Hold speed
4	T, v	L, L	Time headway keeping, speed keeping	Follow behind
5	T, v	I, L	Time headway increasing, speed keeping	Fall behind
6	T, v	D, H	Time headway decreasing, speed keeping	Catch up

Further analyses of clustering results are conducted to figure out variable importance. *Action trends* are illustrated using slope, symbolising the changing rate of a given variable. A positive slope portrays an increasing trend, such as an increase in velocity, while a negative slope implies a decreasing trend. The magnitude of the slope reflects the rate of change. Especially, several adjacent gentle slopes form fluctuations, representing a 'Keeping' trend of variables. Given that variables usually manifest identical trends in different ways, such as linear increase, convex/concave progression, or slightly fluctuating increase, linear regression may struggle to precisely identify variable trends. To capture local trends within specified intervals in dataset and retain overall trend accuracy, we employ a 'sliding window' method (Chu, 1995). A linear regression is computed at each window position, the final slope of the variable data, which serves as the trend index for each variable, is derived by averaging the slopes of these windows. Figure 4 shows the distribution of slopes for each variable in different clusters. The similarity of distributions is evaluated using Kullback–Leibler divergence, which is denoted as $D_{KL}(P||Q)$, measuring how one probability distribution P is different from a second, reference probability distribution Q (Kullback & Leibler, 1951). Results of KL divergence evaluation are illustrated in Figure 5 where the gradient of colour bar from blue to red represents the value from small to large. It can be observed that distributions of v and T in the six clusters have large differences compared to a and Δv, indicating their greater importance in recognising *Action patterns*. This knowledge can be used to manually label *Action patterns* in driving heterogeneity identification.

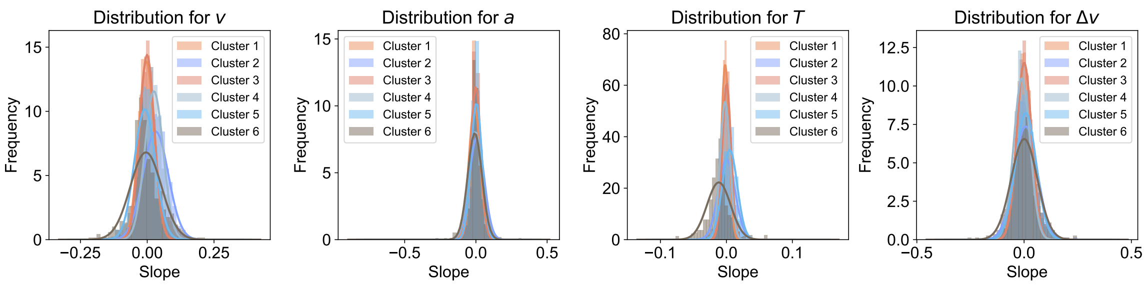


Figure 4: Distributions of variables in each cluster.

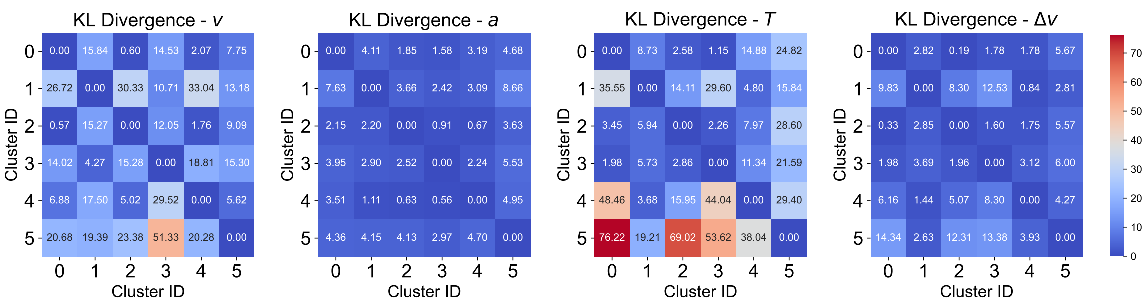


Figure 5: KL divergence of four variables.

5 Conclusions

To capture characteristics of driving behaviour and facilitate identification of driving heterogeneity, this study proposed a method to recognise *Action patterns* based on *Action phases* clustering. Data preparation includes standardising lengths of *Action phases* using a Resampling and Downsampling Method (RDM) and selecting features using PCA. Then, two clustering algorithms, i.e., Agglomerative clustering with dynamic tree cut and X-means clustering, were utilised to distinguish groups of *Action phases*. Six clusters were finally observed, indicating six different *Action patterns* named "Speed up", "Slow down', "Hold speed", "Catch up", "Fall behind", and "Follow behind". Further analyses of clustering results illustrate varied variable importance in *Action pattern* recognition. Velocity v and time headway T exhibit higher importance than acceleration a and speed difference Δv, suggesting that they reflect more characteristics of driving behaviour. The findings of this study provide knowledge to label driving trajectories in driving behaviour analysis, which can help to address label scarcity in supervised learning driving heterogeneity identification and enhance tasks such as driving behaviour modelling and driving trajectory prediction.

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