Automatic extraction of similar traffic scenes from large naturalistic datasets using the Hausdorff distance

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Abstract—Recently, multiple naturalistic traffic datasets of human-driven trajectories have been published (e.g., highD, NGSim, and pNEUMA). These datasets have been used in studies that investigate variability in human driving behavior, for example for scenario-based validation of autonomous vehicle (AV) behavior, modeling driver behavior, or validating driver models. Thus far, these studies focused on the variability on an operational level (e.g., velocity profiles during a lane change), not on a tactical level (i.e., to change lanes or not). Investigating the variability on both levels is necessary to develop driver models and AVs that include multiple tactical behaviors. To expose multi-level variability, the human responses to the same traffic scene could be investigated. However, no method exists to automatically extract similar scenes from datasets. Here, we present a four-step extraction method that uses the Hausdorff distance, a mathematical distance metric for sets. We performed a case study on the highD dataset that showed that the method is practically applicable. The human responses to the selected scenes exposed the variability on both the tactical and operational levels. With this new method, the variability in operational and tactical human behavior can be investigated, without the need for costly and time-consuming driving-simulator experiments.

I. INTRODUCTION

In recent years, multiple open-access naturalistic datasets have been published. Some of these datasets are constructed by first recording videos of traffic with mounted cameras (e.g., NGSIM [1]) or drones (e.g., highD [2] and pNEUMA [3]). Image recognition techniques are then used to extract trajectory data from these videos. Such datasets contain trajectories for all vehicles that pass through a scene. According to Ulbrich et al. [14], a scenario “describes the temporal development between several scenes in a sequence of scenes.,” while “a [traffic] scene describes a snapshot of the environment including the scenery and dynamic elements.” (dynamic elements in the discussed datasets are (human-driven) vehicles). These definitions show that (extracted) traffic scenarios include part of a trajectory. Trajectories that are similar describe the same tactical behavior in most cases. Thus, selecting similar traffic scenarios implicitly means selecting similar tactical responses. Some other approaches even explicitly extract data sometimes referred to as uncertainty) in driver behavior is relevant.

Currently, variability is mostly regarded on the level of operational driving behavior (e.g., [5], [6], [9]–[11]). Operational driving behavior considers the execution of a maneuver [12], for example a lane change. However, variability does also exist on the tactical level, that is, in the choice of maneuver when a driver responds to a traffic scene [12]. For instance, some drivers might respond to a slower-moving vehicle in their lane by overtaking it, while others will brake in the same situation.

Understanding variability on both the operational and the tactical level is important for assessing the human-likeness and acceptability of AV behavior, and also for validating human driver models used in AVs [8]. The reason is that both these applications must consider all possible tactical behaviors under given conditions. Traditional driver models on the other hand, mostly target a specific tactical behavior (e.g., car following in the Intelligent Driver Model [13]), thus for their application, only operational variability is relevant. When designing driver models that describe multiple tactical behaviors, the variability in tactical behavior also needs to be understood.

To study driver behavior variability to its full extent, similar traffic scenes have to be (automatically) extracted from the previously mentioned datasets in order to compare the human responses to these scenes. However, most automatic extraction methods select traffic scenarios (see [4] for a review) not traffic scenes. According to Ulbrich et al. [14], a scenario “describes the temporal development between several scenes in a sequence of scenes.,” where “a [traffic] scene describes a snapshot of the environment including the scenery and dynamic elements.” Dynamic elements in the discussed datasets are (human-driven) vehicles). Thus, selecting similar traffic scenarios implicitly means selecting similar tactical responses. Some other approaches even explicitly extract data
corresponding to a pre-specified tactical behavior (e.g. lane changes in [6], [8]).

These existing approaches expose the variability in the operational execution of a given tactical maneuver but disregard the variability in tactical behavior. Furthermore, including trajectories as part of the automatically extracted data conflates the initial traffic scene (i.e., what a driver is responding to) and the driver’s response itself. This makes it more difficult to investigate the full extent of variability in human responses to a specific initial traffic scene.

A method to automatically extract similar traffic scenes from naturalistic datasets would support studies into driver behavior variability on both operational and tactical levels. With such a method, the trajectories in response to an initial scene can be studied, both in terms of operational and tactical characteristics. However, to the best of our knowledge, all the methods that have been proposed to automatically extract traffic scenarios from the data cannot extract traffic scenes.

This paper proposes a method to automatically extract similar traffic scenes from large naturalistic datasets (for a schematic overview, see Figure 1). To further specify the part of the initial traffic scene relevant for comparing human responses, we introduce the concept of traffic context. We define traffic context as all positions and velocities of all surrounding vehicles at a given time. Compared to the complete traffic scene, the traffic context excludes scenery and the state of the ego vehicle. Therefore, the traffic context represents the aspects of the scene the ego-vehicle is responding to.

Our proposed method hinges on the concept of a distance metric to express the difference between instances of traffic context. We use the Hausdorff distance for mathematical sets [15] as a distance metric to find the closest available scene to a manually-selected example of the traffic context of interest. An implementation of the method is provided on GitHub [16] as an extension of the traffic visualization software TraViA [17]. We validated the method in a case study using the highD dataset, where we show that this method is practically applicable and provides insight into the operational and tactical variability of driver behavior.

II. PROPOSED METHOD

Our proposed method consists of four steps (Figure 1). These steps are briefly introduced in this section and explained in more detail when applied in the case study. In the first step, one should manually select an example of the scene of interest from the dataset. This example represents the traffic scene of interest of which multiple instances should be found. The traffic context from this example is converted to a mathematical set (the context set) in the second step. After that, the Hausdorff distance is used to determine the distance between the traffic context in the selected scene and all other scenes in the dataset. Finally, one selects the N contexts with the shortest distance to the example. The resulting scenes are the scenes with traffic contexts most similar to the example across the whole dataset.

The Hausdorff distance is a distance metric for mathematical sets proposed by Felix Hausdorff in 1914 [15]. It can be used to express the distance between two non-empty compact sets. Many explanations of the Hausdorff distance and how it can be calculated can be found, both in the literature (e.g., [18]) and online. For example, Wikipedia [19] states:

“Informally, two sets are close in the Hausdorff distance if every point of either set is close to some point of the other set. The Hausdorff distance is the longest distance you can be forced to travel by an adversary who chooses a point in one of the two sets, from where you then must travel to the other set. In other words, it is the greatest of all the distances from a point in one set to the closest point in the other set.”

One additional important aspect that we do want to point out, is that the sets compared with the Hausdorff distance can contain a different number of points. This ensures that scenes with different numbers of vehicles can be compared.

III. CASE STUDY: METHODS

In this case study, we make use of the highD dataset [2] to show the potential of our proposed method. The highD dataset consists of traffic data recorded in Germany at 6 different highway locations. The dataset is made up of 60 independent recordings. To visualize the data and generate the images used in this work, we used the TraViA visualization software [17]. The source code implementing the proposed method is publicly available as an extension to TraViA [16].

A. Step 1: select an example

The first step of the proposed method is to select an example of the scene, to which the variability in responses is the topic of research. We will refer to this scene as the traffic scene of interest. This example should be at a specific point in time, seen from the perspective of a selected ego vehicle. For the highD dataset, this means that the example can be fully defined by a combination of three numbers: a dataset id, a vehicle id, and a frame number. For this case study, we have selected the example as depicted in Figure 2. This scene can be found in dataset 1, frame 379 with ego vehicle id 21.

This example was selected because the driver of the ego vehicle (blue, id 21) can respond to this scene in multiple (tactical) ways as illustrated in Figure 2: the driver could decide to stay behind the vehicle it is currently following (id 20), but could also decide to accelerate and overtake that vehicle. The headway between the following vehicles (ids 25 and 26) and the ego vehicle is large enough (95 m and 128.7 m) to allow the ego vehicle to change lanes, but small enough to expect some effect of their presence on the ego vehicle’s behavior.

B. Step 2: extract the context set

The second step of our proposed method is to convert the traffic context to a mathematical set of 4-dimensional points. We will refer to this set as the context set consisting of context points. There is one context point for every surrounding vehicle. The context set can contain any number...
of context points, depending on the number of surrounding vehicles that are assumed to be part of the traffic context. In our case study, we used the definitions provided by highD to determine the vehicles that make up the traffic context. In the highD dataset, 8 positions for surrounding vehicles are reported for every ego vehicle. We assume these surrounding vehicles make up the traffic context.

To convert the state of the surrounding vehicles to context points, the 2-dimensional position of each vehicle is expressed in the ego vehicle’s reference frame. The 2-dimensional absolute velocities (expressed along the same axes) of each vehicle are then concatenated to the relative positions. The result is a 4-dimensional point per surrounding vehicle. In mathematical form, a single context point representing a single surrounding vehicle can be expressed as

\[ p_i = [x_i, y_i, v_{x,i}, v_{y,i}], \]  

where \( i \) denotes the \( i^{th} \) surrounding vehicle, \( x \) and \( y \) denote the center \( x \)-position and \( y \)-position of the vehicle relative to the ego vehicle and \( v_x \) and \( v_y \) the velocities in \( x \) and \( y \) direction.

One potential problem with defining the context points as is done in Equation 1 is that the variability between points will be much greater in the longitudinal (\( x \)) direction than in the lateral (\( y \)) direction. This will be reflected in the Hausdorff distance between the context sets. To give an example, consider the scene in Figure 2. The Hausdorff distance between Figure 2 and another scene where vehicle 20 drives in the left lane will be equal to the distance between Figure 2 and a scene where the gap between vehicles 20 and 21 is one lane-width smaller. Intuitively, there should be a bigger distance in the first comparison. To account for this intuition, we introduce the parameter \( \lambda \) to scale the lateral dimension of the context points. With the new parameter \( \lambda \), the definition of the context points becomes

\[ p_i = [x_i, \lambda y_i, v_{x,i}, \lambda v_{y,i}]. \]  

In our case study, we have assumed \( \lambda = 10.0 \). This corresponds to the notion that a 1 meter change in lateral position of a surrounding vehicle is equally important as a 10 meter change in longitudinal position.

C. Step 3: apply the Hausdorff distance

Now that the traffic context has been represented as a mathematical set, we can use the Hausdorff distance to compare different context sets. This step of the proposed method requires the Hausdorff distance to be calculated between the context set of the selected example and the context sets for all possible combinations of frame number and vehicle id in the dataset. For the highD dataset, there are 39.76 such combinations. Because this is a very large number of distances to be calculated, we will reduce it by filtering the relevant vehicles before calculating the distances.

When searching for scenes with similar traffic contexts, an important aspect is the lane the ego vehicle is driving in. This determines where surrounding vehicles can be present and in which directions the ego vehicle can change lanes (e.g., a vehicle driving in the center lane can go both left and right, but a vehicle driving in the left lane can only change lanes to the right). For that reason we only consider vehicles driving in the same relative lane as the ego vehicle in the selected example. We consider 4 possible relative lanes: the left lane, the center lane, the right lane, and the merging lane. We determine the lane in the selected example (e.g., for Figure 2 the right lane) and only use the vehicle frame combinations from the dataset where the vehicle drives in the same relative lane. For our case study, this leaves 12, 515, 286 vehicle-frame combinations.

If the resulting number of distances to be calculated is still too large after applying this filter, one could consider down-sampling the frames. Depending on the specific frame rate of a chosen dataset, one could assume that the traffic context does not substantially differ within a certain number of frames and therefore only look at a subset of all frames. This would reduce the number of distances to be calculated.
even further. In our case study, this was not necessary because the resulting number of required distance calculations proved to be feasible.

D. Step 4: obtain scenes

When all Hausdorff distances are calculated, the scenes in the dataset that are closest to the example can easily be obtained by selecting the $N$ shortest distances. The only caveat here is that consecutive data frames are very similar, which results in groups with the same vehicle id and many consecutive frame numbers having very similar (short) Hausdorff distances to the example of the scene of interest. This problem can be accounted for by sorting all results based on the shortest distance only keeping the highest entry for every vehicle. Selecting the top $N$ entries from the resulting table yields the final result.

IV. CASE STUDY: RESULTS

We used the proposed method in a case study to extract 250 scenes with a similar traffic context from the highD dataset. The hand-picked example of the scene of interest in step 1 is illustrated in Figure 2. The proposed method resulted in 250 scenes, where the traffic context is closest to this example. The spread of the resulting context points is shown in Figure 3. Of the 250 found scenes depicted in Figure 3, 233 contain precisely 3 surrounding vehicles, the same number as in the scene depicted in Figure 2. The other 17 scenes contain 4 surrounding vehicles.

Figure 3 shows that the proposed method for automatically selecting scenes from a dataset succeeds in selecting context sets that are similar to the traffic context of the scene of interest. Note that the three clusters in this figure are not three independent distributions. The Hausdorff distance between sets can be interpreted as a trade-off between the points in a set. If one is far away from the example, the other two need to be closer to result in a short Hausdorff distance. Therefore, the points within one set cannot be seen as samples from independent distributions.

Figure 3 also shows that the resulting spread is larger in the longitudinal direction than in the lateral direction. For example, in longitudinal positions, the maximum difference between the found sets and the selected example is approximately 25 m where the maximum lateral deviation is approximately 2 m. These values correspond to the used $\lambda$ value of 10.

The variability in the results does depend on the amount of data and the scene of interest. The proposed method finds the closest available sets, so if the example represents a more common scene or the dataset to search in is larger, lower variability in the found context sets can be expected. The variability can also be reduced by selecting fewer context sets i.e. select the $N = 100$ closest set instead of the $N = 250$, but this is a trade-off with the power of the resulting variability estimation.

Among other use cases, these results can be used for research targeting the variability in human responses to similar traffic contexts. To illustrate the utility of the results, Figure 4 shows these human responses: some drivers make a lane change while most remain car following and slow down. The figure also shows kernel density estimations of the longitudinal and lateral distributions for multiple points in time. These estimated distributions could be used to validate driver models that make predictions in the form of distributions. The figure illustrates two potential benefits of the proposed method: the method can be used to extract scenes to which humans respond with different tactical behaviors, and distributions on human behavior can be estimated from the responses to these selected scenes.

DISCUSSION

In this paper, we propose a novel method to automatically extract similar traffic scenes from large naturalistic datasets. In a case study on the highD dataset, we showed that the proposed method is practically applicable and provides insightful results that expose the operational and tactical variability in human responses to similar traffic scenes. Therefore, our proposed method can be a valuable tool for the development of autonomous vehicles and traffic systems that incorporate human responses in their control decisions. Also, the case study showed that humans respond to similar traffic scenes with different tactical behaviors (some change lanes while others stay in their initial lane).

One type of other approaches that are related to our method are those that cluster scenarios. As discussed in the introduction, obtaining similar scenarios serves a different use case than extracting similar scenes. However, clustering requires a distance metric which makes it comparable to our method. There are two specific trajectory clustering methods that bear resemblance to our approach. In [20], the same distance metric is used as in our approach: the Hausdorff distance. However, in their approach, it is used to determine the distance between two trajectories by regarding the way points as a set while we convert the traffic context to a mathematical set. In [21], another distance metric for scenes is proposed based on a grid around the ego vehicle and the longitudinal and lateral distances to other vehicles. Although similar scenes can indeed be found using only longitudinal distance, our method based on the Hausdorff distance is more complete because it also takes into account the lateral positions and longitudinal and lateral velocities of the surrounding vehicles.

Using naturalistic traffic datasets is not the only way to investigate variability in human responses to the same scene, driving-simulator experiments are a well-established alternative. In a driving simulator, multiple participants can be subjected to exactly the same scene with the same traffic context. However, naturalistic data should be used for some applications, for instance when validating human driver models for autonomous vehicles [8]. In other cases, a large diversity of drivers might be needed (e.g., when interested in behavior across the population). This would make driving-simulator experiments time-consuming and expensive. For those reasons, our proposed method based on naturalistic data to study human responses to similar traffic contexts is a valuable new approach.
Fig. 3. The spread of the context points representing the results of the case study obtained after the final step. The top plot shows the positions of surrounding vehicles relative to the ego vehicle (see Figure 2 for the frame definition). The ego vehicle always drives in the right-most lane. The bottom plot shows the absolute velocities of the surrounding vehicles. The ego vehicles velocity is not regarded as part of the traffic context, so it differs for all scenes and is not depicted here. The stars represent the context set extracted from the selected example (Figure 2). The blue dots represent the 250 closest context sets that were automatically extracted from the highD dataset.

Fig. 4. The variability in driver responses (driven trajectories) as they evolve from the 250 traffic scenes with similar traffic context automatically extracted from the highD dataset (represented in Figure 3). The lateral positions are normalized such that 0 m indicates the center of the original (right-most) driving lane. Lane widths differ slightly within the highD dataset, but are approximately 4 m. Blue dots depict the drivers’ initial positions and grey lines depict their individual trajectories - with markers for 1 (orange), 2 (green), and 3 (red) seconds. Distributions on longitudinal and lateral vehicle behavior are estimated and shown on the top and right sides of the figure. The figure illustrates tactical variability: some vehicles (n=19) make a lane change (the red dots with substantial positive lateral positions) while others keep car following in the original lane. Operational variability can also be observed in position and velocity for both the lane-changers and the car-followers.
The proposed approach has four main limitations, some of which can be addressed in future work. First, there is no measure to determine how similar two traffic scenes are from a human perspective. This means that the magnitude of similarities and differences between the selected scenes, and thus the performance of the model, cannot be quantified. The best way to construct such a measure would be to collect similarity ratings from humans by letting them experience selected pairs of scenes from the dataset.

Second, the dimensions of vehicles are not taken into account for the traffic context. This could be addressed in a post-processing step if these dimensions are deemed important to answer one’s research question. This might, however, limit the amount of extracted scenes. Third, the initial velocity of the ego vehicle is ignored. This was done purposefully because we argue that the initial velocity of the ego vehicle is part of the human response, not of the traffic context. This is a limitation when the resulting data is used to validate driver models that do take this information into account. Including the ego vehicle’s velocity could be done by adding the ego vehicle as an extra context point to the context set at position (0, 0, 0).

Finally, there is no systematic approach to determine the parameter $\lambda$. The relative importance of the longitudinal and lateral positions of other vehicles could depend on a number of factors, such as the vehicles’ velocities, road dimensions, and targeted scene. Investigating the influence of the $\lambda$ parameter and developing a systematic approach to determine it can be a subject for future work.

In this paper, we have shown a case study on a single example from the highD dataset. Although we believe it is an illustrative example, it only shows the results of our method for a single scene. In order to validate our approach, it is necessary to investigate other scenes from the highD dataset, we openly share the source code of our method [16]. Future studies can also use this code to systematically investigate the use of our method for different applications and other traffic datasets.

V. CONCLUSION

We conclude that:

- The proposed method, based on the Hausdorff distance, can be used to select scenes with similar traffic context from a large naturalistic dataset.
- With the extracted scenes, the variability in human responses be investigated, independent of the executed maneuver, and without the need for costly and time-consuming driving-simulator experiments.
- Investigating human responses to these scenes (i.e., the trajectories evolving from similar initial conditions) exposes the variability in human responses on both an operational and a tactical level.

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