Affordance-based Computational Model of Driver Behavior on Highways: A Colored Petri Net Approach

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Abstract—In this paper, an affordance-based Colored Petri Net (CPN) model for representing driver behavior is proposed. We adopt a simulation-based approach and conduct an analysis of driver affordances on a highway-driving task. The computational CPN model is an extension of the initial conceptual CPN model and allows experimenters to enforce driving preferences as preferential turn probabilities for individual drivers (risky vs. conservative driver) on the highway system. There are two types of driver models: Confederate Driver Model (CDM) and Subject Driver Model (SDM). Whilst, the CDM follows a pre-scripted path of a confederate driver in actual empirical scenarios, the SDM uses a computational algorithm (implemented within the CPN model) to plan a path based on SDM and CDM affordance derived from attributes such as position, velocity and acceleration. This model allows experimenters to analyze and compare the set of affordances that are available for each driver within this dynamic environment. We conclude by providing a descriptive statistical analysis of the results obtained by comparing the empirical and model-predicted driver data for specific scenarios.

Keywords: Affordance, Driver Behavior Modeling, Colored Petri Net, Simulation.

I. INTRODUCTION

In this paper, we describe a computational model for representing and modeling driver behavior based on the what the environment affords to the driver. It is important to represent, model and understand the behaviors exhibited by drivers within the driving environment as it would allow experimenters to determine the driver decision-making driven by the environmental factors. This would then allow us to inform the design process for automated driving tools and futuristic highway systems.

Gibson [1] defined affordance as the property of the environment that provides an action opportunity for an actor situated within this environment. Many actors reside simultaneously within this environment and perceive a set of available affordances known as a niche. A specific affordance from this niche is then actualized into an action to accomplish the current goal of this actor.

II. LITERATURE REVIEW

In the past, several researchers [2]-[8] have attempted to provide a formalisms to represent and model affordances. In this section, the definition of affordance based on its fundamental properties are described.

A. Definition of an Affordance

There are seven fundamental properties [1],[5] that are helpful in characterizing the nature of affordances.

1. Affordance is an ecological concept that is defined at varying ecological levels for different animal species. However, these levels are determined by the kinds of objects and events that exert selection pressure on that species.

2. Affordances are relational, and are attributed to two or more things taken together. Lombardo [15] suggested the notion of reciprocity to be the essential component of Gibson’s ecological approach to affordances. Reciprocity implies distinguishable yet mutually supportive realities, which relate to asymmetric interdependence, since the relation between the animal and its environment is interdependent yet asymmetric. The environment exists even in the absence of the animal and is a fundamental information source of perceptual structure than the animal. The reciprocity also leads to the complementary relation that exists between an animal and its environment.

3. Affordances are both a fact of the environment and a fact of the behavior of the animal, which according to Gibson [1], informs the animal (perceiver) on how to navigate among things and what to do with them.

4. Sets of affordances constitute niches that specify how an animal lives rather than where it lives (its habitat).
5. Affordances possess real meanings, which exist for things independent of the perceiver.
6. Affordances are invariant combinations of variables within the environment. Affordances are persistent and are always present to be perceived irrespective of whether the perceiver notices them.
7. The observer directly perceives affordances, that are basic, and complex affordances are learned through experience.

Affordance permits “information pickup” and “ecological optics” that act as the tools which facilitate the visual perception of affordances that constrains how an actor perceives things within its environment.

III. PROBLEM STATEMENT

Consider a Highway-Lane-Driver System (HLDS) animal environment system with two highway lanes and an exit lane as shown in figure 1.

Fig. 1. Highway Exit Problem Space.

Assume that, there are two drivers sharing the HLDS, a confederate driver (CD: driver 1) and a subject driver (SD: driver 2). A lane (L_i) within the HLDS provides the affordance “is-drivable” to a driver (d_j), if and only if, the lane is empty for at least three car lengths (assumed safety factor for moving into lane without crashing) at any given time. It is assumed that the drivers possess the capability to perceive the affordances offered by the environment in a concurrent manner, and would therefore be able to decide whether their adjacent lane provides the affordance “is-drivable” or not.

In addition to this, a driver is also capable of perceiving the availability of multiple affordances with respect to other driver (animal) that are part of the HLDS. The spatio-temporal location is inherently specified within the HLDS representation, as the driver would be able to perceive the current lane as well as the position within than lane, which occupied by the other driver within the HLDS. Let us now assume that the goal of both drivers is to exit the HLDS from their respective lanes by maintaining their target speed without crashing into each other. In order to reduce the complexity of this problem space, we also assume that the drivers do not accelerate or decelerate during the course of the scenario. In other words, they are instructed to reach and maintain their target velocity provided to them at the beginning of each test scenario. This problem of exiting the highway is referred to as “Highway Exit” problem space (HEPS). Given this problem description, a consummate formalism is required to represent the affordance structure that exists among these drivers, based on their effectivities and the affordances offered by the highway lanes.

IV. MODELING FRAMEWORK

In this computational model [10]-[12], the drivers possess capabilities (effectivities) that enable them to turn left or right, head straight, accelerate or decelerate. The affordances offered by the HLDS include unoccupied locations on lane 1 (exit lane), lane 2 or lane 3. An invariant combination results from juxtaposing the effectivities of each driver with the lane affordances that are currently available to that driver. This juxtaposition leads to a subset of actions that depict what actions are possible within the current realm of the environment. An actualized action emerges from the driver’s willingness (desire) to execute a specific action from this subset of possible actions.

In order to develop a computational model to represent affordance a Colored Perti Net (CPN) modeling techniques [9] based on the conceptual model framework of HEPS shown in figure 2 was developed.

Fig. 2. Conceptual model framework of HEPS.

The affordance-based CPN model consists of three main component models: Lane Model (LM), Driver Model (DM) and Actualization Model (AM). There are two types of driver models (CDM; SDM) and three identical lane models (one each for lane: Lane 1 [or Exit Lane], Lane 2, and Lane 3). There is also an Initialization Module (IM), which is used to initialize.
the LM based on the driver attributes in CDM and SDM.

In the CPN model, the highway lanes affordances and driver effectivities are represented as place nodes that hold Affordance-type Token (AT) and Effectivity-type Token (ET), respectively. The actualization mechanism is a function represented by a transition node that consumes AT and ET, to produce an Action-type Token (ACT), which indicates the actualized action resulting from the juxtaposition function ($j$).

In the first step, the driver attributes and the lane-block occupancy information for each driver are initialized in the DM and LM, respectively. Then, the complete path information for CD and the initial lane-block occupancy information for SD are input through external files, before the model is executed using the simulation utility within CPN Tools [9]. In the second step, the AM consumes tokens from both DM (CDM and SDM) and LM to generate an actualized action for SD based on the set of lane affordances, turn probabilities and juxtaposition function ($j$). Then, during the final step, the actualized action results in the attributes of SD and CD being updated, which are then passed to the CDM and SDM, respectively.

V. METHODOLOGY

Four experienced test drivers (>15 years of experience) were recruited and randomly grouped into two pairs for the experiment. While one driver was randomly assigned to the role of a confederate driver (CD), the other driver was assigned to the role of the subject driver (SD).

Two independent variables, relative position (both lane and block position) and relative velocity (in blocks/sec) were used to control the settings of each test scenario.

The drivers were randomly assigned to 24 trial sessions comprising of the 12 test scenarios, which were repeated two times each. Prior to beginning of each trial, both drivers received specific instruction about their starting location (initial lane-block position) and the target velocity that they had to maintain for that trial scenario. The overall goals for each driver (i.e., exit the highway, maintain current speed) was also refreshed prior to the beginning each trial.

Four dependent variables (output metrics) were derived from the driver related performance data recorded by the test equipment located in the vehicles driven by both drivers. The dependent variables are $\Delta LP$, $\Delta TD$, $\Delta TTE$ and $\Delta U$. A description of these dependent variables is provided in Table III.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta LP$</td>
<td>Root mean square deviation in the lane position (path) traversed by the human driver and the CPN model at every time update during a given scenario</td>
</tr>
<tr>
<td>$\Delta TD$</td>
<td>Root mean square deviation in the turn direction exhibited by the human driver and the CPN model at every time update during a given scenario</td>
</tr>
<tr>
<td>$\Delta TTE$</td>
<td>Absolute deviation in time to exit (by moving into the exit lane) for the human driver and the CPN model during a given scenario</td>
</tr>
<tr>
<td>$\Delta TD$</td>
<td>Absolute deviation in utilization of the exit lane for the human driver and the CPN model during a given scenario</td>
</tr>
</tbody>
</table>

VI. RESULTS

The data analysis procedure shown in figure 3 would be consistently used to analyze all four dependent variables ($\Delta LP$, $\Delta TD$, $\Delta TTE$ and $\Delta U$) throughout the rest of this section.

The first possible variable that might affect the model’s ability to fit human performance data is “trial” or the human’s amount of exposure to a scenario. Each subject performed a specific scenario twice during the experiment. A dependent t-test will determine whether the fit of the model was significantly different across these two trials. If the dependent variable is not significant (using $\alpha = 0.05$), then data across trials can be aggregated for further analyses.

The next possible variable is “subject” – that is, the two subjects who played the role of subject driver within the experiment. An independent t-test will be used to identify if the model fit one of those subjects significantly better than the other. If the dependent variable is not significant (using $\alpha = 0.05$), then data across subjects can be aggregated for further analyses.

The next possible variable is “scenario”. A general linear model (GLM) based on trial within-subjects and between-subjects effects on dependent variable (output metrics) for each scenario.
performance data significantly better on some scenarios than on others. If the F-statistic for the between-subjects effects were found to be significant (using \( \alpha = 0.05 \)), then this would indicate that the model fit the data of one subject better than the other did, for that dependent variable. If the F-statistic for the within-subjects effects were found to be significant (using \( \alpha = 0.05 \)), then it would mean that there was a significant effect due to scenario on the model predicted value for the dependent variable being analyzed. This justifies a further need for investigation on that dependent variable. Then, further post-hoc analyses could be conducted to determine exactly which scenarios led to particularly good or bad predictions by the model and identify any emerging patterns.

The twelve scenarios were grouped into the different categories based on the starting lane position (whether CD was vertically closer to exit lane), starting block position (whether CD was horizontally closer to exit lane) and relative velocity (whether SD was driving faster than CD).

A. Lane Position

In this section, the data related to the root mean square deviation in the lane position (\( \Delta LP \)) occupied by the human subject driver and CPN model predictions are analyzed. The summary of the test results for \( \Delta LP \) are shown in Table IV.

<table>
<thead>
<tr>
<th>Effects</th>
<th>Test Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within subject effect due to Trials</td>
<td>SD1: t-Statistic = 1.736, p-value = 0.110</td>
</tr>
<tr>
<td></td>
<td>SD2: t-Statistic = 0.019, p-value = 0.984</td>
</tr>
<tr>
<td>Between subjects</td>
<td>t-Statistic = -1.714, p-value = 0.100</td>
</tr>
<tr>
<td>Within-subject Effects due to Scenario</td>
<td>F-Statistic = 1.764, p-value = 0.18</td>
</tr>
<tr>
<td>Between-subjects Effects due to Scenario</td>
<td>F-Statistic = 13.151, p-value = 0.171</td>
</tr>
</tbody>
</table>

The paired t-tests for each driver, SD1 (t-statistic = 1.736, p-value = 0.110) and SD2 (t-statistic = 0.019, p-value = 0.984) appears to indicate that there seems to be no significant effect on \( \Delta LP \) due to trial for both drivers.

Second, the independent t-test (t-statistic = -1.714, p-value = 0.100), indicates that each subject driver appears to have no significant effect on the deviation in lane position.

Finally, the results on the F-test appears to indicate that seems to be no significant within-subjects effect (F-Statistic = 1.764, p-value = 0.18) or between-subjects effect (F-Statistic = 13.151, p-value = 0.171) on \( \Delta LP \) due to the scenario. This implies that the model appears to be consistent in predicting the lane position between subject drivers on all scenarios.

B. Turn Direction

The summary of the test results related to the root mean square deviation in the turn direction (\( \Delta TD \)) are shown in Table V.

<table>
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</thead>
<tbody>
<tr>
<td>Within subject effect due to Trials</td>
<td>SD1: t-Statistic = -0.411, p-value = 0.688</td>
</tr>
<tr>
<td></td>
<td>SD2: t-Statistic = -0.268, p-value = 0.793</td>
</tr>
<tr>
<td>Between subjects</td>
<td>t-Statistic = -0.200, p-value = 0.843</td>
</tr>
<tr>
<td>Within-subject Effects due to Scenario</td>
<td>F-Statistic = 2.953, p-value = 0.043</td>
</tr>
<tr>
<td>Between-subjects Effects due to Scenario</td>
<td>F-Statistic = 2288.784, p-value = 0.013</td>
</tr>
</tbody>
</table>

The paired t-tests for each driver, SD1 (t-statistic = -0.411, p-value = 0.688) and SD2 (t-statistic = -0.268, p-value = 0.793) appears to indicate that there seems to be no significant effect on \( \Delta TD \) due to trial for both drivers.

Second, the independent t-test (t-statistic = -0.200, p-value = 0.843), indicates that each subject driver appears to have no significant effect on the deviation in lane position.

Finally, the results appear to indicate that there seems to be a significant within-subjects effect (F-Statistic = 2.953, p-value = 0.043) and between-subjects effect (F-Statistic = 2288.784, p-value = 0.013) on \( \Delta TD \) due to the scenario. This result is expected because the model is not expected to make a turn at the exact same time as a human driver during any given scenario. In addition to this, both drivers turned the car and moved into an adjacent lane only while making a lane change, which makes this output measure more sensitive. However, the overall lane position occupied by both drivers was closely predicted by the model.

C. Time to Exit

In this section, the results related to the absolute difference in the time taken for SD to move into the exit lane are summarized in Table VI.

The paired t-tests for SD1 (t-statistic = 1.914, p-value = 0.081) and SD2 (t-statistic = 1.448, p-value = 0.175) indicated that there was appears to be no significant effect on \( \Delta TTE \) due to trial for both subjects.

The independent t-test (t-statistic = 1.281, p-value = 0.213), indicated that each subject driver had no significant effect on \( \Delta TTE \).
The results appear to imply that there seems to be a significant within-subjects effect (F-Statistic = 2.936, p-value = 0.044) but no significant between-subjects effect (F-Statistic = 37.87, p-value = 0.103) on ∆TTE each scenario.

The significance in within-subjects effect on ∆TTE is attributed to the errors of commission and omission [13],[14] performed by a subject driver during a test scenario. For instance, a SD may incorrectly perceive that an exit lane is inherent blocked by CD (error of commission) or completely fail to pursue a lane change maneuver (error of omission) during a close-call situation thereby adding to ∆TTE. In such a situation, the model pursues a riskier path, and is capable of judging precisely whether an affordance is available to be actualized it into an action. This minimizes the deviation in ∆TTE.

D. Utilization of Exit Lane

In this section, the results related to the absolute difference in the utilization of the exit lane (ΔU) for SD are shown in Table VII.

<table>
<thead>
<tr>
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<th>Test Statistic</th>
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<tbody>
<tr>
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<td>Between subjects</td>
<td>t-statistic = 1.281, p-value = 0.213</td>
</tr>
<tr>
<td>Within-subject Effects due to Scenario</td>
<td>F-statistic = 2.936, p-value = 0.044</td>
</tr>
<tr>
<td>Between-subjects Effects due to Scenario</td>
<td>F-statistic = 37.87, p-value = 0.103</td>
</tr>
</tbody>
</table>

The paired t-tests for SD1 (t-statistic = 1.811, p-value = 0.097) and SD2 (t-statistic = -1.668, p-value = 0.123) indicated that there was no significant effect on ΔU due to trial on both subjects.

Second, the independent t-test (t-statistic = -1.196, p-value = 0.244), appears to indicate that the subject drivers had no significant effect on ΔU.

Finally, the results indicate that there appears to be a significant within-subjects effect (F-Statistic = 3.231, p-value = 0.032) but no significant between-subjects effect (F-Statistic = 43.074, p-value = 0.096) on utilization of exit lane due to each scenario. This implies that the model appears to be inconsistent in predicting the values of ΔU within-subjects on one or more scenarios. However, the model appears to be consistent in predicting the values of ΔU between-subjects (both subject drivers) on all scenarios.

VII. CONCLUSION

In this paper, we presented a need for a computational formalism to represent and model affordances. Then, we introduce the HEPS domain to analyze driver behavior and affordances that become available to drivers on highway systems. We introduced a computational model based on CPN techniques, which is capable of predicting the ΔLP, ΔTD, ΔTTE and ΔU and analyzed the deviation to verify the precision of the CPN model. Finally, we present the results of our analysis and show how the model predicts driver behavior on a sample set of twelve empirical highway driving scenarios. We conclude by arguing that this computational model based on affordances would serve as a very effective tool to model and represent affordance based driver behavior on highway systems.

VIII. FUTURE WORK

We propose to construct the formative affordance space for the set of available affordances, which would represent the niche and indicate the available region of travel for the drivers on highways based on their environmental affordances.

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