Synthesizing Personalized Training Programs for Improving Driving Habits via Virtual Reality

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Figure 1: A user is practicing with a personalized training program synthesized by our approach to improving her driving habits via virtual reality. Left: our system is constructed using a Logitech driving controller and a FOVE eye-tracking virtual reality headset, via which the user's driving and eye gaze data are collected for analyzing her driving habits. Right: A training program (blue route) is synthesized by our approach for improving the user's driving habits via different traffic events.

Abstract

The recent popularity of consumer-grade virtual reality devices, such as Oculus Rift, HTC Vive, and Fove virtual reality headset, has enabled household users to experience highly immersive virtual environments. We take advantage of the commercial availability of these devices to provide a novel virtual reality-based driving training approach designed to help individuals improve their driving habits in common scenarios.

Our approach first identifies improper driving habits of a user when he drives in a virtual city. Then it synthesizes a pertinent training program to help improve the users driving skills based on the discovered improper habits of the user. To apply our approach, a user first goes through a pre-evaluation test from which his driving habits are analyzed. The analysis results are used to drive optimization for synthesizing a training program. This training program is a personalized route which includes different traffic events. When the user drives along this route via a driving controller and an eye-tracking virtual reality headset, the traffic events he encounters will help him to improve his driving habits.

To validate the effectiveness of our approach, we conducted a user study to compare our virtual reality-based driving training with other training methods. The user study results show that the participants trained by our approach perform better on average than those trained by other methods in terms of evaluation score and response time and their improvement is more persistent.

Index Terms: Virtual Reality—Modeling and Simulation—Driver Training Simulator

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1 Introduction

Driving safety is a critical issue throughout the world. According to the Global Road Safety Status Report published by the World Health Organization, although the road quality all over the world has improved over the past decade, there are still 1.25 million deaths caused by road traffic accidents every year. As the report shows, in the past three years, the death toll of driving accidents has increased in 68 countries. Noted by the director-general, Margaret Chan, of the WHO, "The loss caused by road traffic accidents is unacceptable." It is crucially essential to reduce traffic accidents.

There are many causes of traffic accidents, including poor road conditions, bad weather and road emergencies. In particular, bad driving habits, such as forgetting to signal before making a turn, or failing to look at the rear-view driving mirrors before changing lane, significantly increase the risk of accidents.

Conventionally, people learn about driving safety rules through a handbook and from a coach before getting a driving license. Unfortunately, bad driving habits could develop after one obtains his driving license. With the development of virtual reality technologies, some driving schools have introduced virtual reality-based driving training. However, this type of training usually focuses on normal driving circumstances only and does not consider the diversity of driving habits. It could facilitate teaching people how to drive, rather than correcting driving habits. Our novel personalized driving training approach provides a solution for the latter.

Besides, existing virtual reality-based driving training usually uses a virtual reality headset for visualization purposes only. The user's visual data such as his eye gaze during the simulation is not collected, which could be very useful for analyzing user's driving habits. In contrast, our approach makes use of FOVE as shown in Figure 1, a consumer-grade virtual reality headset equipped with eye-tracking capabilities, for collecting the eye gaze data of the user for analysis to synthesize a personalized training program.

Our work employs a novel optimization approach to synthesize personalized training programs with traffic events relevant to improving one's driving habits. As Figure 1 shows, our approach can synthesize a training route based on a user's problematic driving habits identified from a pre-evaluation. The user can learn to amend his driving habits from different kinds of traffic events encountering along the synthesized route. For instance, if the user tends not to signal before turning, our optimization will synthesize a route which frequently requires the user to practice signaling before making a turn. Through adjusting the weight associated with each consideration in the optimization, a variety of routes can be synthesized with different numbers of turns, pedestrians and other road entities. By this immersive virtual reality training experience, the user can effectively improve his driving habits.

The major contributions of our work include the following:

- Proposing a novel optimization-based approach to synthesize personalized training programs tailored for improving targeted driving habits.
- Demonstrating that consumer-grade virtual reality headsets with eye-tracking capabilities (e.g., FOVE) can be effectively employed for virtual reality-based driving training. The collected eye gaze data is highly applicable to analyze user's driving habits.
- Evaluating our approach by comparing with other training methods in terms of improving driving habits persistently.

2 Related Work

We provide a succinct overview of the traditional driving safety training approaches and review previous works about driving simulations in virtual environments.

2.1 Traditional Driving Safety Training

We focus our discussion on safety training for correcting bad driving habits. Studies found that bad driving habit is one of the most common causes of motor vehicle accidents [20, 24]. Blows et al. [5] examined the relationship between risky driving habits, prior traffic convictions, and motor vehicle injury. They found that those who have risky driving habits are more likely to have been injured while driving over the same period. For novice drivers who do not have good hazard perception [29] or elder drivers who do not have good eyesight and response speed associated with age [2], the risk of accidents is even larger.

Traditional methods of driving safety training include reading driving handbooks, watching training videos and teaching by a driving coach. Most people who have a driving license probably have the experience being criticized by a driving coach for poor driving habits such as forgetting to signal before making a turn or forgetting to look at the rear-view driving mirrors. The major goal of driving safety training is to amend problematic driving habits and to reinforce preparedness for the emergency. However, a lot of rules with texts or in videos are difficult to follow and remember during daily driving.

Our approach plays the role of an individual driving coach, which discovers mistakes and bad habits of a user during the driving automatically. A followed personalized training program is figured out to correct mistakes and improve improper driving habits. The engaging, immersive experience helps users remember the correct driving habits, which they can apply to real driving. Compared with traditional driving safety training methods, driving training in virtual environments is much more safe, convenient and economical.

2.2 Driving Simulations in Virtual Environments

Driving simulation has been widely employed in different domains for studies related to engineering, medicine, and psychology, as well as driving training. Ruiz et al. [28] used driving simulator scenarios for road validation studies. Lee et al. [19] used a driving simulator to analyze the risk of older drivers in encountering motor vehicle crashes. Besides, some researchers even used driving simulators for clinical studies like evaluating the sleepiness of drivers or training the driving after stroke [1, 9, 15].

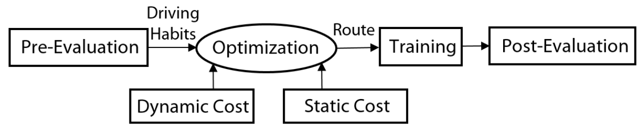


Figure 2: Overview of our approach.

Research has been conducted on comparing driving on a road and driving through a simulator. Underwood et al. [34] did an experiment about hazard detection both for driving on the road and through a simulator. Godley et al. [16], and Bella et al. [3] compared the speed in the two driving scenarios. Besides, Trnros et al. [33] analyzed driving behaviors in a real and a simulated tunnel. Findings from these works show that driving through a simulator shares substantial similarity with driving on a real road.

The promising use of driving simulations for mimicking real-world driving has led researchers to devise more sophisticated techniques for conducting driving simulations. Cremer et al. [10] worked on the problems of driving scenario and scene modeling for virtual environments based on the Iowa Driving Simulator (IDS). Bella et al. [4] created a collision warning system for rear-end collision in a driving simulator. With an effective driving simulator, researchers can also conduct more sophisticated driving behavior analysis. Calvi et al. [8] analyzed driver performance on deceleration lanes. Crundall et al. [11] found that commentary training could improve responsiveness to hazards in a driving simulator. Musselwhite et al. [23] assessed the improvement of older people's driving behavior via computer-based training packages. Roenker et al. [27] found that simulator-trained drivers improved on the skills of changing lane and using signals properly. Besides, some works show that the driver's visual attention also plays an important role in driving simulation. Konstantopoulos et al. [18] used a driving simulator to explore drivers eye movements under daytime, nighttime and raining conditions. Friedland et al. [14] used a driving simulator to test the performance of the glare-reducing device. Pradhan et al. [26] used eye movements to evaluate the effects of the driver's age on risk perception through a driving simulator. Leeuwen et al. [21] researched on the changes of gaze patterns of novice drivers during 30-minute simulator-based training.

A major advantage of using virtual reality and simulation for driving training is that it enables practice under hazardous conditions. Compared to previous works, especially the driving simulation for training [6, 13], our approach focuses on training people to correct problematic driving habits and to handle traffic events properly rather than only teach general rules or car manipulations. Inspired by the works of Huang et al. [17] and Darken et al. [12], our approach employs an optimization framework to synthesize a personalized training program. However, our optimization incorporates specific design factors encoding the user's driving habits identified from the pre-evaluation. By controlling the weights associated with different training objectives and design criteria, one can synthesize a variety of personalized training programs with routes optimized for correcting the problematic driving habits of the user. Inspired by the traffic simulation works of Sewall et al. [30, 31], our approach designs a rich variety of traffic events in a virtual environment, providing users with highly realistic learning experiences.

3 Overview

Figure 2 shows the overview of our approach. First, the user undergoes a pre-evaluation test from which his driving habits are recorded and analyzed. Our system computes a pre-training score which represents the driving performance of the user. Next, our optimizer makes use of the driving habit analysis results to synthesize a person-

(a) Cars

(b) Main Street

(c) Crossroad

(d) Pedestrians

Figure 3: Examples of street scenes.

alized route containing multiple traffic events designed for correcting different problematic driving habits. The optimization considers a dynamic cost that accounts for dynamic events occurring along the route, as well as a static cost that accounts for static entities along the route. The user then receives the training by driving through the synthesized route in virtual reality. Finally, he takes a post-evaluation test where his driving performance is re-evaluated and represented as a post-training score. The post-training and pre-training scores are compared to validate if there is any improvement in driving performance.

4 Virtual Environment Modeling

4.1 Driving Habits

In an evaluation, the user goes through a driving simulation using our virtual reality setup. Throughout the simulation, the user needs to handle multiple traffic events based on which his driving habits are determined. The simulation lasts about three minutes. For example, in an event about changing lane, the user needs to change lanes to pass a slow-moving vehicle. As the user attempts to change lanes, our system records the behavior of the user, to examine whether he signals correctly and whether he looks at the rear-view driving mirrors as determined from the eye-gaze data collected from FOVE (Figure 10). As the evaluation test needs to solicit the comprehensive driving habits of the user, the driving simulation contains all four types of traffic events. Figure 4 shows a partial map of the city used for evaluation with the regions of traffic events highlighted.

We use California Driver Handbook as reference to judge the correctness of the user's driving habits and controls recorded from an evaluation. Table 1 lists six driving habits which our system evaluates in our experiments. Each driving habit is scored between 0 and 1, and represented by s_i where i is the ID of the habit labelled in Table 1. The driving habit score is computed based on the percentage of times the user responds properly to a traffic event corresponding to the driving habit.

In our experiments, a user takes a pre-evaluation, goes through a personalized training program synthesized by our approach, and then takes a post-evaluation. His pre-evaluation and post-evaluation scores are compared to determine if the training leads to any improvement in his driving performance. Also, in each evaluation, we record the response time of the user in handling a sudden event.

4.2 Traffic Element

Object. We construct virtual environments with Unity 5.6. Figure 3 shows examples of urban street scenes used in our experiments. We obtain all models of road, building and car used in our experiments from the Urban City Pack and the Traffic Cars Pack in the Unity Asset Store.

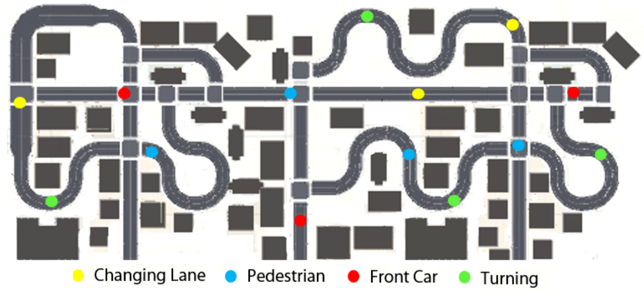


Figure 4: The partial map of the city used for pre-evaluation. The city contains 40 events categorized into four groups based on the driving habits that they solicit.

#	Driving Habits
1	Look at the rear-view mirrors before turning
2	Look at the rear-view mirror before changing lanes
3	Signal before turning
4	Signal before changing lanes
5	Stop for pedestrians
6	Decelerate when passing a crossroad

Table 1: Driving habits analyzed in the pre-evaluation test.

To simulate traffic, we control the motion of vehicles and pedestrians by scripts. The scripts control vehicles to steer, stop and turn, similarly to the pedestrians motion. The iTween plugin is used to compute smooth movement paths for vehicles.

Traffic Event. In our experiments, we include four kinds of common traffic events: changing lane, pedestrians crossing a road, stopping of a frontal car and making a turn. These events are designed to help the driver to amend the bad driving habits. The user's driving habits play an important role in handling traffic events which could happen out of a sudden. For instance, in the event about pedestrians, the driver may come across a pedestrian running across a road. This event can help the driver to develop the driving habit about stopping for pedestrians.

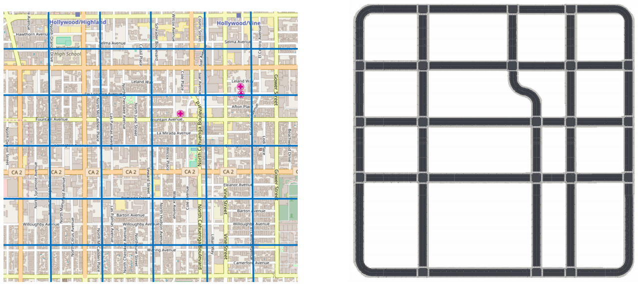
4.3 Urban Layout for Training

Figure 5(b) shows an urban layout we use for the training part, which is generated from the Open Street Map of a block in Los Angeles shown in Figure 5(a). The generated layout is composed of main streets extracted from the input map. For simplicity, we do not use the small streets from the input map in creating the layout.

We describe the details of our approach for generating the layout for training using an input map (e.g., an Open Street Map). First, our approach applies Hough Transform algorithm to detect and extract main streets (yellow and orange in Figure 5(a)) on the input map.

Second, our approach divides the input map uniformly into cells. In Figure 7(a), we divide the map into 36 uniform cells. A cell may contain a straight road, a turn, a crossroad and so forth.

Third, using a database of road templates which covers different road types such as two-lanes straight roads, four-lanes straight roads, turns and crossroads, our approach matches each cell on the map with the most similar road template. We use the following steps to find a matching cell: (a) Judging which type of roads the cell contains. (b) Detecting the directions of the roads in the cell. (c) Choosing the road template with the most similar road type and directions from the database. Figure 6 shows two examples about the compatibility of road templates. An urban layout is generated as each cell is converted into a road using the most-similar road template. We define forty types of templates in total.



(a) Open Street Map (b) Generated Layout

Figure 5: An example of generating a layout map from Open Street Map. (a) The map is divided into cells as the input. (b) Our approach detects the main streets (yellow and orange) through Hough Transform algorithm and generates a layout map.

Fourth, buildings and trees are added to fill in the blocks. In this step, our approach calculates the size of each blank region. Then it randomly chooses buildings with appropriate sizes from the Urban City Pack and adds them to the blank regions.

5 Route Synthesis

Our personalized training program is based on urban street scenes showing several kinds of traffic events aimed at correcting different driving habits. Our approach synthesizes a route which guides the drivers to go through these events. The route is synthesized based on the problematic driving habits of the user identified from the pre-evaluation. We discuss the optimization framework in Section 5.3. After the optimization, a personalized route is generated.

Figure 7 shows the route synthesis process, including two stages:

- **Initialization.** The layout map of the city is uniformly divided into cells same as in Figure 5(b). For example, the map in Figure 7(a) is divided into 36 cells, and each cell is represented as an information node. The node stores the score information and connectivity information used for the optimization.
- **Optimization.** The optimization begins and proceeds iteratively. At each iteration, a route is synthesized by sampling over the map, and the quality of the route is evaluated according to a number of cost functions. The optimization iterates until a route which meets the design goals is synthesized. Figure 7(b) shows a synthesized route that can be used for training via virtual reality simulation.

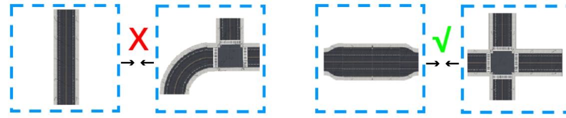
5.1 Representation

The information of each cell is stored as a node. A route is represented as a sequence of nodes. Each node has four scores: straightness score, turning score, pedestrian score and car score, ranging from 1 to 5. For example, if a cell contains lots of turns or crossroads, the turning score is very high (e.g., 5). If the cell contains only a few pedestrians, the pedestrian score is low. Besides, a node also stores connectivity information about nearby cells for judging if the node sequence can form a route.

5.2 Cost Function

We define a cost function $C_{\text{total}}(R)$ to evaluate the quality of a synthesized route R. Our cost function has two major components: dynamic cost C_{dynamic} and static cost C_{static}. The dynamic cost encodes the factors related to the cars and pedestrians on the roads that can move during the simulation. The static cost encodes the factors related to the road layout, namely, the number of turns and the straightness of the roads.

As the experiments of Brooks et al. [7] show, prolonged driving simulations could lead to simulator sickness. Therefore, we also include a regularization cost $L(R)$ as a soft constraint. This cost



(a) Incompatible (b) Compatible

Figure 6: Compatibility between road templates. (a) A pair of incompatible road templates. (b) A pair of compatible road templates.

regularizes the length of the synthesized route such that it is not too long, so as the training time. The total cost function is given by:

$$C_{\text{total}}(R) = w_{\text{static}} C_{\text{static}}(R) + w_{\text{dynamic}} C_{\text{dynamic}}(R) + w_{\text{length}} L(R), \tag{1}$$

where R represents the current synthesized route composed of a sequence of nodes like $(r_1, r_2, ..., r_n)$. $C_{\text{total}}(R)$ denotes the total cost function of the optimization. $C_{\text{static}}(R)$ and $C_{\text{dynamic}}(R)$ denote the static and dynamic costs. $L(R)$ is the regularization cost which is defined as the length of the route R. w_{static}, w_{dynamic} and w_{length} are the weights of the respective cost terms.

Static cost. The static cost encodes factors related to the road layout. We can control the proportion of turns and straight roads along the synthesized route by adjusting the parameters λ_S and λ_T of this cost function:

$$C_{\text{static}}(R) = \lambda_S \lambda_T - \frac{1}{5|R|}(\lambda_S \sum_{r \in R} F_S(r) + \lambda_T \sum_{r \in R} F_T(r)), \tag{2}$$

where $|R|$ represents the numbers of nodes in route R; r refers to a node in route R; $F_{\text{S}}(r)$ and $F_{\text{T}}(r)$ return the straightness score and turning score of node r respectively. Essentially, the cost term evaluates the sum of straightness scores, and the sum of turning scores along route R. λ_{S} and λ_{T} are parameters for controlling the importance of the straightness score and the turning score. $\frac{1}{5|R|}$ is a normalization term (the maximum value of scores $F_S(r)$ and $F_R(r)$ is 5).

Dynamic cost. The dynamic cost encodes the consideration of dynamic elements such as cars and pedestrians that appear in the simulation. We can control the number of cars and pedestrians appearing along the route by adjusting parameters λ_{P} and λ_{C} of this function:

$$C_{\text{dynamic}}(R) = \lambda_{\text{P}} \lambda_{\text{C}} - \frac{1}{5|R|}(\lambda_{\text{P}} \sum_{r \in R} F_{\text{P}}(r) + \lambda_{\text{C}} \sum_{r \in R} F_{\text{C}}(r)), \tag{3}$$

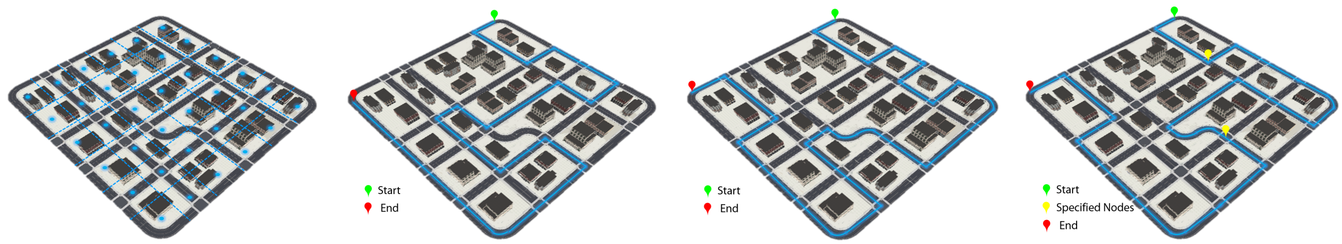
where $F_{\text{P}}(r)$ and $F_{\text{C}}(r)$ return the pedestrian score and car score of node r respectively. Essentially, this cost term evaluates the sum of pedestrian scores, and the sum of car scores along route R. λ_{P} and λ_{C} are parameters for controlling the importance of the pedestrian score and the car score. $\frac{1}{5|R|}$ is a normalization term.

Weight and Parameter Settings. To generate a personalized training program, the weights and parameters are set according to the driving habit scores s_i of a user obtained from the pre-evaluation test.

We set the weight of static cost as $w_{\text{static}} = 5 - s_1 - s_2 - s_3 - s_4$, since the first four types of driving habits are related to the static layout of the roads. Similarly, we set the weight of dynamic cost as $w_{\text{dynamic}} = 3 - s_5 - s_6$, as the last two types of driving habits are related to the dynamic events of the pedestrians and cars.

The parameters of $\lambda_S, \lambda_T, \lambda_P$ and λ_C are calculated corresponding to the scores of straightness, turning, pedestrian, and car during the pre-evaluation process.

λ_S constrains the numbers of straight roads, which tends to help the user to form the habits of looking at the rear-view mirrors and



(a) Initial Map (b) Synthesized Route (c) Route with More Turns (d) Specified Nodes

Figure 7: An example of route synthesis. (a) The initial map consisting of 36 cells. (b) A route synthesized by our optimization with $\lambda_S, \lambda_T, \lambda_P$ and λ_C setting as 1. (c) A route with more turns with λ_T adjusting from 1 to 3. (d) A route optimized to go through some nodes (yellow) specified by the user.

signaling before changing lanes. As the traffic events about changing lanes happen on straight roads, the user can receive more training about the relevant driving habits with a larger λ_S. Accordingly,

$$\lambda_S = 3 - s_2 - s_4. \tag{4}$$

λ_T constrains the number of turns, which helps the user to form the habits of looking at the rear-view mirrors and signaling before turning:

$$\lambda_T = 3 - s_1 - s_3. \tag{5}$$

λ_P constrains to the number of pedestrians, which helps the user to form the habit of stopping for pedestrians:

$$\lambda_P = 2 - s_5. \tag{6}$$

Finally, λ_C constrains the number of cars, which helps the user to form the habit of decelerating when passing a crossroad. To provide the user with more opportunities to practice the habit of reducing speed when passing a crossroad, λ_C is set as large to include more cars at the crossroad if he does not possess the habit. Accordingly,

$$\lambda_C = 2 - s_6. \tag{7}$$

We set the weight of regularization cost as $w_{\text{length}} = 0.05$ by default, yet it could be adjusted to increase or decrease the desired length of the synthesized route. We show different syntheses generated by using different weights and parameters in our experiments.

5.3 Optimization

Figure 7 illustrates the route synthesis process. The start point and end point of the route are pre-specified. The goal is to synthesize a route that minimizes the total cost function. To explore the space of possible routes effectively, an MCMC (Markov chain Monte Carlo) optimization approach based on simulated annealing is applied.

At the initialization, a route which connects the starting point to the end point is randomly sampled. At each iteration of the optimization, a new route R' is sampled by altering the current route R as follows: a random pair of nodes r_a and r_b along the current route is selected, and the sub-route connecting this random pair of nodes like $(r_a, ..r_i, ..r_b)$ is replaced by another randomly sampled sub-route like $(r_a, ..r_j, ..r_b)$. Our approach computes the sub-route by randomly sampling the nodes sequence between r_a and r_b on the premise such that the sequence of nodes can still form a route. Then, the newly sampled route R' is evaluated using the total cost function, which may or may not be accepted depending on the acceptance probability of R' calculated by the Metropolis criterion:

$$Pr(R'|R) = \min(1, e^{\frac{1}{T}(C_{\text{total}}(R) - C_{\text{total}}(R'))}), \tag{8}$$

where T is the temperature of the simulated annealing process. T is high at the beginning of the optimization, allowing the optimizer to explore the solution space more aggressively; T is low towards the end of the optimization, allowing the optimizer to refine the solution.

Changing the Importance Parameters. In this optimization, we experiment with adjusting the importance parameters λ_S and λ_T, which can change the proportion of turns and straight roads. Figure 7(c) shows a route which has more turns. Before the optimization, we adjust the λ_T from 1 to 3. Thus, the optimizer has a higher probability to accept a route with more turns like this one. Akin to synthesizing a route with more turns, we can use a larger λ_S to synthesize a route with more straight roads.

As we adjust the parameters λ_P and λ_C in the dynamic cost function, we can also synthesize a route with different proportions of pedestrians and cars. As Figure 8 shows, the blue line which represents the result synthesized with $\lambda_C = 3$ has more cars along the route, compared to the orange line which represents the result synthesized with $\lambda_C = 1$. Similarly, as Figure 8 shows, the green line which represents the result synthesized with $\lambda_P = 3$ has more pedestrians along the route, compared to the red line which represents the result synthesized with $\lambda_P = 1$.

By adjusting the weights, the designer can apply our approach to synthesize a personalized training route with the desired traffic events or layout of roads, to correct the targeted driving habits.

Passing Specified Locations. Sometimes, we may need to synthesize a route which passes specified locations. This can be achieved by adding a hard constraint in the sampling process, to check if the specified locations are included in the sampled route R'. If not, the optimizer will directly reject the route R'. Figure 7(d) shows an example where two locations (in yellow) are specified by the designer as ones that the synthesized route must pass through. The optimizer synthesizes a route that satisfies this hard constraint.

6 Experiments

6.1 Implementation

We implemented our approach using C# and Unity 5.6. We ran our experiments on a PC equipped with 16GB of RAM, a Nvidia Titan X graphics card with 12GB of memory, and a 2.60GHz Intel i7-5820K processor. The user experienced the simulation via the FOVE, a consumer-grade eye-tracking virtual reality headset. The FOVE can track the user's eye gaze, from which our program checks if the user has looked at the rear-view driving mirrors during the evaluation and training.

6.2 Training and Evaluation

We evaluate the effectiveness of our virtual reality training approach and compare with other training approaches.

Participants. We recruited 50 participants, whose driving experiences ranged from 1 to 20 years. The participants were randomly divided into 5 groups. Each group has 10 people and corresponds to a training condition described below.

Training. We describe the training procedure under each of the training conditions.

For the ***Personalized VR*** group, each participant was asked to follow the synthesized personalized training route to drive for 15

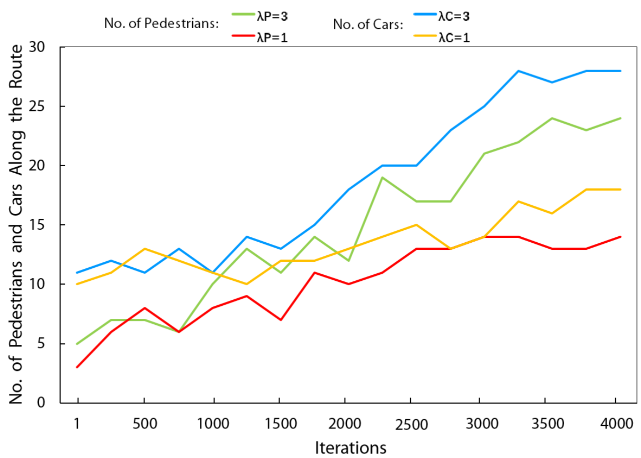


Figure 8: Number of pedestrians and cars along two routes synthesized using different weights λ_P and λ_C. Larger λ_P and λ_C result in more pedestrians and cars along the route.

minutes. During the training, he encounters several types of relevant traffic events specific to his driving habits identified in the pre-evaluation and the corresponding warning message showed. For instance, if the participant does not stop for pedestrians, traffic events like a pedestrian running across the road will be triggered when the user's car enters the trigger zone. Besides, he will receive a warning as "slow down".

For the ***Traditional VR*** group, each participant was asked to take a traditional VR driving training, which akins to the design of [6, 13]. Each participant is asked to drive along a random route for 15 minutes, where the route is not a personalized one. The other parts of the program are the same with Personalized VR group.They also receive a warning when improper driving behaviour happens.

For the ***Video*** group, each participant was asked to watch a driving control and safety training video, which showed the correct driving controls when the drivers encountered different types of traffic events we considered in our work. The participant could watch the video for as many times as he wanted to remember the details of the instructions within 15 minutes.

For the ***Manual*** group, each participant was asked to read a driving handbook. The handbook provided details and pictorial illustrations about the correct and safe driving habits. Each participant could read the manual for 15 minutes.

For the ***None*** group, the participants did not go through any training.

Post-Evaluation. Each participant was asked to do two post-evaluation tests where he would drive a car on the urban streets via our virtual reality setup. The simulation for each post-evaluation needs about three minutes. The first test was done right after training. The second test was done a week after training. Before doing a test, no matter which training condition the participant went through, he was asked to familiarize himself with the control of the FOVE virtual reality device in a warm-up session until he felt familiar with the control. This typically took about 5 to 10 minutes.

Metrics. We collected the following metrics to evaluate and analyze the performance of the participants in the tests:

- **Evaluation Score:** We recorded the problematic driving habits, such as not signaling before making a turn and not reducing the speed when coming across a pedestrian. Each problematic habit reduces its associated score as described in Section 4.1. The higher the scores, the better the training effect.

  We also tracked if the user looked at the rear-view mirror before turning or changing lanes. Figure 10 shows a screenshot of the rear-view driving mirrors with the eye gaze points. To achieve this, our approach tracks the participant's eye gaze using FOVE.

- **Response Time:** We measured the response time, which reflects whether participants are sensitive to emergencies. The response time is defined as the time interval between two time stamps: an event starting to happen and the participant starting to response to the event. For instance, when a participant is passing a bus, a pedestrian runs out in front of the bus. The response time is the time interval between the pedestrian starting to run and the participant starting to brake.

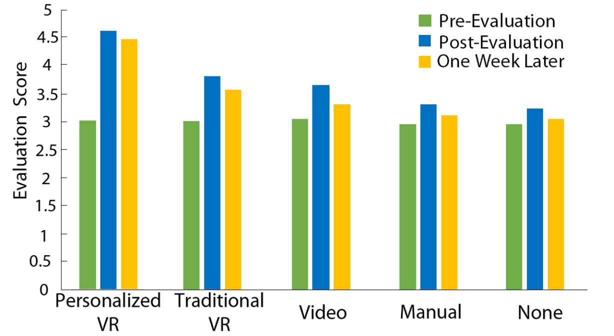


Figure 9: The results of evaluation scores in our user study, obtained from a pre-training evaluation, a post-training evaluation and an evaluation conducted one week later. The value of each bar represents the mean.

7 Results and Discussion

We discuss the results of different training approaches. Specifically, we evaluate the participants' performance in terms of evaluation score and response time, before and after the training. Figure 9 shows the scores the participants obtained after different types of training.

7.1 Evaluation Score

Our approach detects six types of driving habits via Logitech driving controller and Fove in the evaluation. The calculation of evaluation score is the same with Section 4.1.

Pre-Evaluation Results. The green bars in Figure 9 show the pre-evaluation scores of the 5 groups that would undergo different training conditions. The average scores of different groups are close, showing that each group of participants had similar levels of driving skills before training. This group of results is the baseline of our experiments.

Post-Evaluation Results. The blue bars in Figure 9 show the evaluation scores after training. The Personalized VR group got the highest scores (M=4.6, SD=0.56), followed by Traditional VR group (M=3.8, SD=0.75), Video group (M=3.65, SD=0.78), Manual group (M=3.3, SD=0.75) and None group (M=3.25, SD=0.92). The results suggest that the Personalized VR approach is more effective than the other approaches in terms of improving driving skills.

It is interesting to look at the standard deviations of the results after training. In general, the Personalized VR group performed consistently better as reflected by smaller standard deviations (SD=0.56), while those trained with other conditions had more fluctuating performance as reflected by larger standard deviations. This may suggest that the training with Traditional VR group(SD=0.75), Video group (SD=0.78), Manual group (SD=0.75) are not efficient for some participants. On the contrary, the standard deviation of the scores received by the participants trained with our approach is smaller, where most participants got improvement in the training.

Figure 10: The user's eye gaze tracked by the FOVE virtual reality headset. Our system detects whether the user has looked at the rear-view driving mirrors (red). His eye gaze (green) is recorded from the FOVE virtual reality headset for analysis.

We also did the T-test between our approach and other four methods. We used an alpha level of 0.05 for all statistical tests. The results show that the Personalized VR group got higher evaluation scores (M=4.6, SD=0.56) than Traditional VR group (M=3.8, SD=0.75, p=0.016), Video group (M=3.65, SD=0.78, p=0.007), Manual group (M=3.3, SD=0.75, p=0.0004) and None group (M=3.25, SD=0.92, p=0.001) in statistics. It indicates that the training effect of our approach were significantly greater than other training methods.

Results after a Week. According to the Ebbinghaus Forgetting Curve, which models the decline of memory retention against time, humans generally forget about 75% of knowledge they have learned after one week. Thus, to investigate how well the participants retained the knowledge they learned under different training conditions, we conducted another evaluation test one week after the training session.

The yellow bars in Figure 9 show the results one week after training. The participants who underwent the Personalized VR training achieved similar performance as they did one week ago (M=4.45, SD=0.55). The performances of the participants trained by the Traditional VR approach (M=3.55, SD=0.69), a video (M=3.3, SD=0.71) or a safety manual (M=3.1, SD=0.56) dropped in general, while they still showed some improvement over those who were untrained (M=3.05, SD=0.57).

7.2 Response Time

Figure 11 reports the mean of the response time obtained in the pre-evaluation (green), post-evaluation (blue) and evaluation conducted one week after the training(yellow). Our system records 3 response times of participant per evaluation.

The difference between pre-evaluation and post-evaluation illustrates the effect of training. The Personalized VR group has the greatest improvement on response time with reduction from 0.79 to 0.58 seconds, comparing with 0.80 to 0.65 seconds for Traditional VR group, 0.92 to 0.76 seconds for Video group, 0.85 to 0.73 seconds for Manual group, and 0.83 to 0.72 seconds for None group.

The standard deviation of Personalized VR group (SD=0.16) is also smaller than Traditional VR group (SD=0.81), Video group (SD=0.87), Manual group (SD=0.86) or None group (SD=0.69) after training. Since during the pre-evaluation process, if the users have longer response time, they will get lower scores on some driving habits (e.g., stop for pedestrians). The lower scores on the corresponding habits lead to synthesized routes with more relevant traffic events by our optimization. Thus, our approach is efficient for most participants on the aspect of shortening response time.

In the T-test about the response time, we still set the alpha level as 0.05 for all statistical tests. The Personalized VR group has shorter response time (M=0.58, SD=0.16) than Traditional VR group (M=0.65, SD=0.81, p=0.04), Video group (M=0.76, SD=0.87, p=0.004), Manual group (M=0.73, SD=0.86, p=0.0005) and None group (M=0.72, SD=0.69, p=0.005) in statistics. We can find from the results that the improvement about response time of our approach were significantly greater comparing with other training methods.

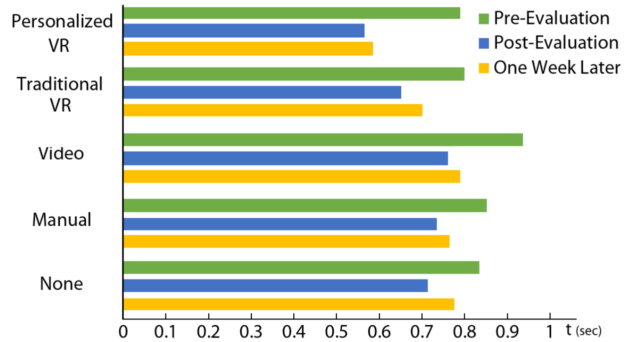


Figure 11: The results of response time in pre-evaluation, post-evaluation, and evaluation one week later. The value of each bar represents the mean. The shorter the bar, the shorter the mean of response time, hence the better the training effect.

The yellow bars in Figure 11 show the response time in the evaluation of one week after training. The Personalized VR group maintained almost the same level as post-evaluation. Whereas the other groups show increasing on the response time, and their response time almost fell to the level of those who were untrained. The Personalized VR training approach leads to a more persistent training effect.

8 Summary

We introduced a personalized, virtual reality-based approach for improving driving habits, which can more effectively train a user to possess good driving habits and to become more attentive and responsive, compared to traditional training approaches.

Additionally, there are several major benefits of using a personalized virtual reality training approach over traditional approaches. First, the realistic, immersive training experience offered by virtual reality allows the participant to learn by practicing directly, hence avoiding the gap between theory and practice in traditional training approaches. We believe that our virtual reality training approach can complement traditional training approaches. Second, our approach synthesizes a personalized training program based on the pre-evaluation results. It plays the role of an individual driving coach, who can figure out a targeted solution for an individual to amend his bad driving habits. Third, different from the handbook and video training which lack interactivity, a virtual reality training approach which is often more appealing. By conducting the virtual reality training in a serious game setting, the participant may feel more motivated to receive training.

Limitations. As the participants did not go through real-world evaluations, we can not firmly conclude about their performance in real driving after different training. However, we believe that our experiments and results are still meaningful and indicative because our experiments were conducted in realistically-modeled scenes and through a driving controller that mimics a real-world driving setup.

Besides, our VR simulation is an uni-sensory system, which only considers the vision sense. Although other senses (e.g., auditory, tactility) have impacts on driving, the dominance is far lower than vision [32]. Under VR environment, we can not ensure the user has the same emotion state with real driving because the user is not afraid of crash anymore. We may add a real driving evaluation in future work to avoid this factor.

Our approach has considered six common types of driving habits; future extension should include other types of driving habits that could be related to traffic accidents. In our current setting, all the events about cars and pedestrians are controlled by scripts, which happen only when the user enters the trigger zones. The AI scripts could potentially be replaced by agent models that simulate the realistic movement of pedestrians and cars [36] driven by real-world data [35]. As we used FOVE, a consumer-grade VR device, to perform the experiments, the immersiveness offered could be less compared to that offered by a professional-grade setup like a CAVE.

We believe our personalized virtual reality driving training could complement conventional driving training by a coach. Using our approach, the user can focus on reinforcing certain driving habits according to his areas of weakness, and that he can practice repeatedly at a low cost. However, we believe that practicing with a coach on real roads is necessary for the user to master all the basic driving skills for handling real-world scenarios, some of which are still difficult to simulate.

Future Work. It will be interesting to explore using a more realistic 3D street scene to perform our experiments. For example, one may use a 3D-reconstructed street scene for conducting evaluation and virtual reality-based training. As the resolution of such 3D-reconstructed scenes continues to grow, a virtual reality-based training in such scenes could be very realistic. One may also use a professional 3D modeling engine like the CityEngine to procedurally generate a realistic-looking city [25] for evaluation and training.

Besides the present work on car driving training, our approach can also be generalized to other training targets, e.g., aircraft driving, safety training [22]. Similarly, the approach can evaluate the performance of a user at first and find their shortcomings. Then a training program can be generated via optimization. Inspired by Xie et al. [37], we can even synthesize training program for exercising.

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