HindSight: Enhancing Spatial Awareness by Sonifying Detected Objects in Real-Time 360-Degree Video

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Technical Report No. UCB/EECS-2018-190
http://www2.eecs.berkeley.edu/Pubs/TechRpts/2018/EECS-2018-190.html

December 19, 2018

Acknowledgement

I would like to thank my advisor, Professor Björn Hartmann, for his invaluable guidance, mentorship, and inspiration. I would also like to thank James Smith, without whom this work would not have been possible. Special thanks to the many friends and colleagues who have supported me during this project. Finally, I would like to thank my family for their continuous love and support.

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by Eldon Schoop

Submitted to the Department of Electrical Engineering and Computer Sciences, University of California at Berkeley, in partial satisfaction of the requirements for the degree of **Master of Science, Plan II**.

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12/14/2018

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ABSTRACT
Our perception of our surrounding environment is limited by the constraints of human biology. The field of augmented perception asks how our sensory capabilities can be usefully extended through computational means. We argue that spatial awareness can be enhanced by exploiting recent advances in computer vision which make high-accuracy, real-time object detection feasible in everyday settings. We introduce HindSight, a wearable system that increases spatial awareness by detecting relevant objects in live 360-degree video and sonifying their position and class through bone conduction headphones. HindSight uses a deep neural network to locate and attribute semantic information to objects surrounding a user through a head-worn panoramic camera. It then uses bone conduction headphones, which preserve natural auditory acuity, to transmit audio notifications for detected objects of interest. We develop an application using HindSight to warn cyclists of approaching vehicles outside their field of view. To evaluate HindSight, we first conduct an exploratory study with 15 users. We next create a VR platform to simulate realistic traffic scenarios and use it to evaluate HindSight in a controlled user study with 21 participants. Participants using HindSight had fewer collisions, increased their space to other vehicles, experienced reduced cognitive load, and reported a perceived increase in awareness.

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

Author Keywords
360-Degree Video; Computer Vision; Sonification; Augmented Perception

INTRODUCTION
The human visual system has both biological and cognitive constraints. Our vision spans a usable field of roughly 114 degrees [17], and our anatomy restricts our sharpest, foveal vision to a field of only 5.2 degrees [47]. Cognitively, as we become absorbed in a task, our "locus of attention" narrows [38]; i.e., we tune out external stimuli, increasing our focus but possibly drowning out important events such as alarms or environmental dangers. Interfaces which can redirect a user's attention to these overlooked stimuli have the potential to prevent serious accidents. Our research goal is to supplement these sensory constraints by augmenting spatial awareness for objects that are outside of a person's visual field.

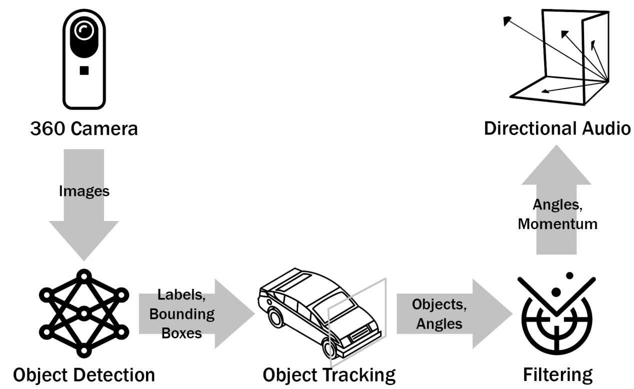

Figure 1. HindSight uses a neural network to detect objects from live, ego-centric 360-degree video, a filter bank to extract relevant ones, and a application-specific sonification program to convey results to a user.

Some approaches substitute all information for specific senses– e.g., by using a head-mounted display to show a LIDAR point cloud [30] or a live 360-degree video stream [2]. Repurposing the visual system is potentially powerful, but such systems are not easily integrated into daily activities because they require an adaptation period before use and can create hurdles in social interactions. We seek to develop a system that enhances spatial awareness by redirecting attention without impeding natural senses.

We introduce HindSight, a wearable system that increases spatial awareness by detecting relevant objects in live, ego-centric 360-degree video and sonifying their location and properties through bone conduction headphones. Our approach draws upon advances in computer vision to identify points of interest in a user's surroundings, and work in delivering continuous feedback for physical tasks to notify the user when necessary to redirect their attention.

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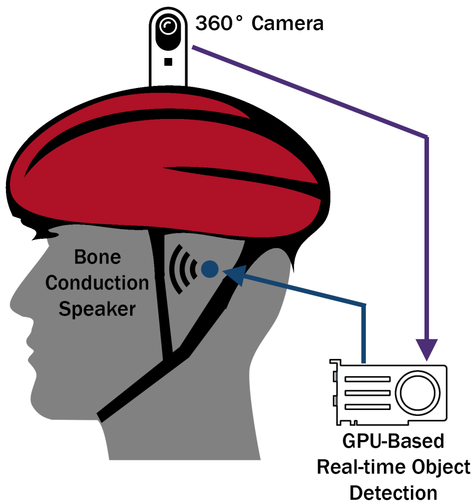

Figure 2. HindSight uses a spherical camera mounted to a bike helmet to capture a user's surroundings. Video is streamed to a laptop worn in a backpack.

HindSight streams 360-degree video from a head-worn camera to a real-time object detection neural network running on a laptop worn in a backpack (Figure 2). The system filters output from the neural network and picks the most relevant objects for the application. These objects are sonified, conveying attributes such as their type, location, and velocity. The user hears this audio through Bluetooth wireless bone conduction headphones, which transmit vibrations directly through the skull. The key benefit of using bone conduction is it leaves the ears unobstructed, enabling retention of normal auditory acuity.

We develop an application for HindSight: a program to augment cyclists' sensory ability by warning users of vehicles which are approaching in a potentially dangerous way. We calculate potential danger by attributing momentum and direction data to oncoming vehicles outside the cyclist's field of view. The momentum and direction data of vehicles approaching the cyclist are used to calculate a directional "danger" metric, which is sonified by modulating beeps using panning (to indicate direction) with tempo and pitch (to indicate danger). We provide a technical evaluation of our system to measure its precision and the window of usable time a cyclist has to react to its output. On average, we find HindSight detects potentially unsafe approaching vehicles 1.89 seconds ($\sigma = 0.40$) s before they would hit the bicycle.

We conduct an exploratory user evaluation with 15 participants to determine how users perform with our system. When comparing our system to the control condition, users reported perceived increases in safety ($\mu = 4.00, \sigma = 0.82$), time to react ($\mu = 3.73, \sigma = 0.57$), comfort ($\mu = 3.47, \sigma = 0.96$), and awareness ($\mu = 3.53, \sigma = 0.96$), on a 5-point Likert scale. Several participants noted our system detected potential dangers they would have otherwise missed: *"[HindSight could] sense the danger from the views that people not normally see"* (P4). Open-ended feedback revealed areas for potential improvement: *"If it could detect danger slightly (just slightly) sooner, that would be better"* (P14). On a 5-point Likert scale, users expressed they would use the system during their real commutes if it was available ($\mu = 3.87, \sigma = 0.96$).

Figure 3. HindSight was designed to be comfortable to wear in everyday cycling scenarios.

To safely conduct controlled user evaluations of HindSight, we create a VR-based simulator which can run scripted traffic scenarios. We use the simulator to conduct a controlled user evaluation with 21 participants. We found, with HindSight activated, participants experienced fewer collisions (2, as opposed to 7), increased their distance to surrounding vehicles, and had decreased cognitive load. Participants echoed the results of the exploratory study, expressing perceived increases in safety ($\mu = 4.10,\ \sigma = 0.70$), reaction time ($\mu = 4.05,\ \sigma = 0.74$), and comfort ($\mu = 3.67,\ \sigma = 0.97$).

In summary, we contribute: (1) The HindSight real-time computer vision system for detecting and sonifying objects of interest in 360-degree body-worn video; (2) an application of Hindsight for augmenting cyclists' spatial awareness; (3) a technical evaluation and exploratory evaluation of this application; and (4) a controlled user study within an immersive VR simulation of the HindSight system.

RELATED WORK

HindSight builds on prior work in three primary areas: devices that enhance spatial awareness, systems which provide real-time feedback for physical tasks, and tools for interpreting 360-degree video.

Enhancing Spatial Awareness

Devices which enhance spatial awareness ingest information from a user's surroundings, process it into a meaningful representation, and output it via visual, audio, or haptic displays.

Augmenting Field of View

We are inspired by systems such as FlyViz, which augments a user's field of view by displaying reprojected 360-degree panoramic video into a Head-Mounted Display (HMD) [2]. FlyViz effectively remaps a user's surroundings to their visual field, but requires an adaptation period before it can be used comfortably. The Skully motorcycle helmet [49] projects a rear-facing camera feed onto a transparent HMD. LiDARMAN takes this idea further by projecting a 3D point cloud from a head-mounted Lidar scanner into an HMD [30]. Closely related to our work is SpiderVision, which blends front and rear-facing video feeds into an HMD based on motion detected behind the user [12]. Rather than use motion to trigger additional visual input, HindSight identifies objects around a user and determines if they are important enough to redirect the user's attention. HMD-based solutions face multiple hurdles to real-world use. First, HMDs have limited resolution and field of view compared to natural human vision. Second, social acceptability of their continual use is not yet established. Finally, some users additionally experience *virtual reality sickness* when using VR headsets and HMDs [31]. In contrast to this prior work, while we us an HMD as an apparatus in our user studies, HindSight exclusively uses audio for output during use.

Assistive Technology

Assistive devices for the visually impaired ingest visual or spatial data and encode this information into a different sensory output, such as audio or vibrotactile displays.

Systems to aid the visually impaired often employ sonification techniques to help users create a mental representation of their surroundings. As early as 1974, Sonar has been used to sonify obstacles in front of a user as a navigation aid [19]. Depth and color of objects in a scene can be sonified with rich audio, such as orchestral instruments, [13]. We draw upon this work to develop our sonification framework, but focus on objects *outside* of the user's visual field. HindSight is not designed to *replace* the visual system, but, rather, *augment* its capabilities.

Varying degrees of computational intelligence can be used to extract higher-level information from images, from relying on remote human assistance to on-device or cloud-based machine learning tools. VizWiz uses on-demand, crowdsourced support to answer visual questions for pictures taken from a smartphone [3]. Computer vision algorithms can help users discriminate objects [11], locate visual markers [55], and describe scenes with machine-generated natural language [51]. Depth cameras can be used to create an interactive map of the user's surroundings [22] and identify obstacles in real-time, such as unoccupied chairs and walls [52]. HindSight uses machine learning based object detection to identify objects outside of a user's visual field and alert them when necessary. The goal of HindSight is not to show *all* object information, but only *relevant* objects which require attention.

Enhancing Awareness in Traffic

Our cycling application builds off related work in increasing awareness of traffic situations. Projected AR displays have been used to alert other drivers of a cyclist [18, 5] and display a "safety envelope" where others may pass the bicycle [8]. Audio [41, 21] and haptic [10, 1] feedback can increase driver awareness of other vehicles. Sonification can increase detectability of approaching vehicles in environments with background noise [20, 27], especially in the case of quiet electric vehicles [29, 28]. Diedrichs and Parizet separately describe design principles for sonifying approaching vehicles, such as amplitude modulation, pitch, and rhythm [10, 36]. HindSight leverages these design principles to generate audio to alert the user of oncoming vehicles outside their visual field.

Real-Time Feedback for Physical Tasks

Actions taken in the physical world can entail a sense of *risk*, i.e., actions are often irreversible, and may potentially harm the user if performed incorrectly [23]. HindSight operates in the physical world, and our cycling application exhibits this type of risk. We are inspired by digital fabrication devices that provide real-time feedback to reduce or mitigate risk.

Devices can make users aware of variables that are relevant to a task but not readily perceivable by a person. Projected AR visualizations can reveal the otherwise invisible forces inside CNC machines [35] or warn users when they are drilling too far into a surface [43]. Haptic feedback can alert users to take corrective action when cutting a block of material if they are approaching the edges of a predetermined model [56]. HindSight draws upon the metaphor of using real-time feedback to display variables in the environment and suggest the user take corrective action. In particular, our cycling application provides audio feedback to redirect the user's attention to potentially dangerous situations, prompting the user to take corrective action if necessary.

Exploring and Interpreting 360-degree Video

360-degree video captures information from the camera's entire surrounding area, which can be explored by users manually or interpreted with computer vision algorithms. Research systems have allowed users to annotate prerecorded 360-degree video [37] or explore streaming video in real-time from a head-worn camera array [33]. Deep neural networks have also been used to correct skew in 360-degree video [50]. Computer vision techniques have been used to recognize the faces of speakers in 360-degree videos and generate a simulated "multi camera" output [42]. Pano2Vid generalizes this approach, simulating human motion of an artificial camera to track areas of interest in 360-degree video [48]. HindSight utilizes computer vision techniques to detect objects in 360-degree video and requires a 360-degree camera to dynamically adjust the analyzed field of view when head orientation changes from travel direction, i.e., the user does not look straight ahead.

HindSight uses monocular, optical sensing to detect vehicles. This is one of several possible techniques that have been used in the literature [45, 32]. One distinguishing feature of our approach is that we use a panoramic camera which captures the relative angle of each pixel, yielding accurate direction information for detected vehicles.

HindSight DESIGN CONSIDERATIONS

At a high level, HindSight seeks to enhance the spatial awareness of users while preserving their ability to rely on unaugmented sensory input. Our technique was guided by several overarching guidelines:

Do not impede natural sensory input: For safety and social acceptability, we aim to preserve real-world sensory input. This precludes uses of opaque HMDs and suggests audio or haptic displays. However, audio stimuli that block out environmental sound are not appropriate. To satisfy these guidelines, we rely on delivering audio notifications through bone conduction headphones, which leave the ear canals unobstructed. It is possible for users to perform auditory and visual tasks at the same time [15], so we believe audio to be a proper interface for a warning system for bicycle users.

Importantly, cyclists may not always be able to rely on natural audio cues, e.g., in dense traffic or in urban areas where sound is reflected from multiple facades. In these situations, HindSight could provide additional, resolvable audio cues.

Provide real-time interpretation: Extracting higher-level information from a scene can provide more concise, semantically meaningful information to users. We use a computer vision pipeline to recognize objects in the environment and only sonify detected objects that are of critical importance.

Be conservative in information delivery: The system should only engage the user when important and necessary. The level of display should be proportional to the importance of the message, i.e., ramp up the level of warning with the level of danger. Our sound design is further informed the particularities of bone conduction headphones.

Designing Audio for Bone Conduction

Using bone conduction as our information display poses several design challenges over traditional headphones because audio does not enter the user's ear canal, but is instead transmitted through the user's skull through vibrations. The primary benefit is that bone conduction headphones can be worn safely in situations where the users must still use their ears as an important channel for information.

The primary goal of our sound design for our cycling application is to provide a clear auditory message to the user of our system that there is a danger in their vicinity. We design the audio such that it can transmit three key dimensions of information to the user: direction, proximity, and type of danger. We use Hermann et al.'s sonification framework [15] together with principles from SAFERIDER [10] to inform our design decisions, as described below.

Parameterizing Information

Auditory displays fall into the broad categories of alarms, status indication, data exploration, and entertainment [15]. HindSight is an alarm system, because its primary purpose is to indicate the presence of a dangerous object. HindSight has properties of *safety auditory displays*, which prompt for corrective action, and *imminent auditory displays*, which alert when time-critical corrective action is needed [10].

We map our three primary dimensions of information (direction, proximity, and type of danger) in the following ways:

Direction is mapped to directional audio: We aim to assist the user in localizing that object by mapping the direction of the dangerous object to directional audio, so that they can respond to it appropriately. Because of the limited effectiveness of using binaural audio with bone conduction headphones (described below), we use panning to convey spatial information.

Distance to the detected object is mapped to tempo and pitch: We take inspiration from parking assist and cross traffic alert systems in automobiles, which emit a sequence of beeps of increasing tempo as the car is approaching obstacles (or vice versa). As an object approaches the user, we play its requisite sound at a faster rate and increase its pitch. This is chosen to create a sense of urgency in the user as the object approaches, prompting the need for time-critical corrective action [10].

Types of objects are mapped to different timbres: Categorical types of data should be represented by changing acoustic variables like timbre. This makes it easier for users to isolate different sounds and still resolve the direction of these sources. The pitches of the sounds we play range between 500Hz and 2000Hz, proportional to an object's danger level. This range transmits clearly using our bone conduction headphones, and the 2000Hz pitch has been recommended for urgent safety indicators [10].

Only Show Two Objects at Once: Timbre and directional audio are two of the best ways to help users resolve multiple simultaneous sound sources [15]. However, we found it is easy to get overwhelmed with information when more than two moving objects are represented with audio. Therefore, we constrain our system to display only up to the two most dangerous objects to limit the amount of cognitive load placed on the user.

We also design for several particularities of bone conduction:

Exploit the Boundary between Haptics and Audio: Lower frequencies render almost haptically on bone conduction headphones, providing vibrating sensations at the contact points with the user's head. We exploit this property by overlaying low frequency sounds in our audio to help direct the user's attention to the direction of the audio.

Use Panning Instead of Binaural Spatialization: Standard audio spatialization algorithms do not work well for bone conduction, making it difficult for users to resolve the direction of spatialized audio. This is due to the fact that most audio spatialization software uses Head-Related Transfer Functions (HRTF) to determine what audio should go to each ear. HRTFs are calculated based on a model of the user's ear and head size, and assume that audio is entering through the ear canal. In our application, audio is passed to the ear drum through the skull. Because humans skulls have different acoustic properties, existing HRTFs are not appropriate [7].

As a workaround to this limitation, we lower the dimension of data by instead panning the audio between the left and right channels of the bone conduction headphones. This provides reasonable directional feedback (users can still resolve the general direction of danger) at the cost of not allowing as many unique angles of direction.

SYSTEM ARCHITECTURE

Our system consists of a 360 degree video camera attached to a bicycle helmet, connected via USB to a laptop in the user's backpack. The laptop is connected to a pair of bone conduction headphones via bluetooth.

Image Acquisition

We acquire a stream of 1280 x 720 pixel equirectangular images at 15Hz using a Ricoh Theta S camera and process them using OpenCV.

Figure 4. Detected objects at intermediate filtering stages of HindSight: (1) The neural network outputs bounding boxes of detected objects. (2) Objects are tracked frame-to-frame. (3) Only objects moving nearer to the user are kept. (4) Only object approaching the user are kept.

The equirectangular image format projects a spherical image onto a rectangular image by mapping latitude coordinates of the spherical image directly to x pixel coordinates, and longitude values directly to y pixel coordinates [46]. A major downside to this format is that the image distorts near the poles, but minimizes distortion near the equator.

To obtain the best classification performance, we process each frame of video before passing it to our object detector. For our application, the top and bottom 27° of the image generally contain no useful data (the user's helmet and the sky) and are removed. The rest of the image is cut into three parts to produce nearly square images, which minimizes aspect ratio distortion and increases performance with our object detector. These partitions overlap slightly to aid resolving objects which traverse their boundaries.

Object Detection

We use the YOLOv2 neural network to detect objects because it provides accurate, low latency predictions [40]. We additionally considered SSD [25], which achieved similar performance, but with higher latency on our particular hardware.

Using pretrained model weights, YOLOv2 is capable of classifying 80 labels, several of which are traffic related: e.g., car, truck, bus, bicycle, person, stop sign, traffic light. The output from this step is a list of bounding boxes, labels, and confidence values. The object detector is generalizable to new classes of objects through retraining on example images of desired classes. Classification takes about 50 ms when using the down sampled input images described earlier.

All classification is done in real time on a laptop carried in the user's backpack. The laptop is an Origin EON17-SLX with an Intel i7-6700K 4.0 GHz processor, 16GB DDR4 RAM, and a GeForce GTX 980 video card with 8GB DDR5 RAM running Windows 10. Software used are Python 3.6, Tensorflow with CUDA extensions enabled, and OpenCV 3.2. The high-performance GPU of the laptop is critical in order to run a deep neural network such as YOLOv2 in real time.

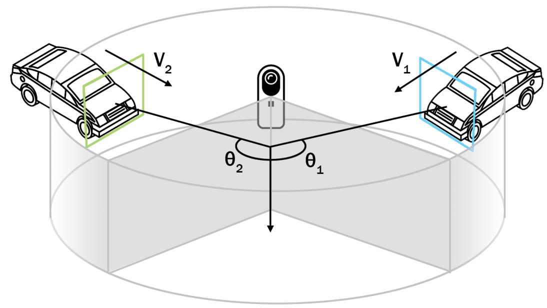

Figure 5. HindSight only notifies users of objects which are approaching and outside of their field of view. We approximate the human visual field to 110°.

Object Tracking

Output from YOLOv2 provides us with no frame to frame coherence of objects, i.e., there is no way to tell if any bounding box in two frames correspond to the same underlying object. Frame to frame tracking is important because we wish to filter objects based on their behavior. We developed a simple and fast algorithm for approximating the most likely bounding box for a given object between two frames, with acceptable accuracy. Our algorithm greedily merges weighted object bounding boxes over a sequence of frames, "remembering" previous merges.

Object Filtering

Several filters are applied to the set of tracked objects to narrow down which objects the user might find the most important. The type of filtering applied depends heavily on the application that the system is used for. The following filters are used for the bicycle in traffic scenario. For each filter, we manually count objects falsely identified as dangerous over a 21-second training video clip and report the number of these false positives.

Only Accept Vehicles Outside the User's Visual Field

Our first filter eliminates objects irrelevant to cycling in traffic from consideration (e.g., toasters, airplanes, clocks). We also eliminate any objects that are in the front 110 degrees of the user's visual field (slightly less than human peripheral vision). This is trivially calculated because the camera position tracks the user's gaze, as a *head-stabilized* configuration [4].

Only Display Growing Objects

Objects with bounding boxes decreasing in size over time can be assumed to be moving away from the user, and likely pose no danger. We calculate the square root of the area of each bounding box over a time period of 10 frames (approx. 300 ms) of video and fit a linear function to approximate the growth of the bounding box. If the slope of this line is positive, then the area of the box is trending larger, and the object is coming closer to the user. Any object with a negative area-growth slope is removed from consideration. The growth filter reduces the number of false positives from 122 (vehicle filter only) to 46 in our sample data.

Orientation Filtering

For our application, objects that are approaching the user from behind pose the most risk, and any object that is moving away from the user in their direction of travel most likely passed by them. We thus reject objects which are not traveling in the direction of the user from behind them. The orientation filter reduces the number of false positives to 4 in our sample data.

We determine the latitude of an object by considering its center point and subtract 180 from it to determine its angle from the rear of the user. We then take the absolute value of this to determine absolute angle from the rear of the user.

$$\sphericalangle_{user} = \mathrm{abs}(\sphericalangle_{object} - 180)$$

We fit a linear function to these values over a window of 10 video frames, in parallel with the object growth filter (the orientation filter does not introduce additional delay). If the slope is positive, the object is most likely moving toward the user from behind. We filter out any object with a negative slope from consideration, leaving only objects moving in the direction that the user is looking. An IMU attached to the user's helmet can base this calculation on the direction of travel as opposed to the direction the user is facing by offsetting the center point (180°) by the head orientation value.

Removing Additional False Positives

We apply a final filter that requires an object to have made it through the previous filters for at least 3 frames. This minimizes briefly appearing misclassfied objects, as well as any object that erroneously passed through the set of filters. The averaging filter reduces the number of false positives to only 1 (a parked car) in our training video sample.

After all filters are applied, we calculate a danger metric that is roughly proportional to each object's momentum. This is equal to an approximation of the object's mass times the rate at which the bounding box is growing.

$$D_i = \underset{x}{\mathrm{argmax}}(M_{x,i}V_{x,i})$$

Where D_i is the most dangerous object for frame i, $M_{x,i}$ is the approximate mass, and $V_{x,i}$ is the object's bounding box growth rate in frame i.

Audio Output

Output from the filtering process goes into an audio system that synthesizes and spatializes sounds based on which objects are considered the most dangerous. Audio is sent over Bluetooth to AfterShokz Trekz Titanium bone conduction headphones.

Sounds played to the user were authored in FL Studio 12, a professional digital audio workstation. A virtual loopback MIDI interface, loopMIDI, was loaded onto the laptop to allow our software to communicate with FL Studio. Custom MIDI control messages were specified to allow our software to start, stop, and spatialize various sounds. FL Studio listens for these messages and controls audio playback accordingly. The benefits of this approach are the robustness it provides when trying different user interfaces. Any software that can listen to MIDI can respond to our system, providing a many ways our system can connect to various actuators.

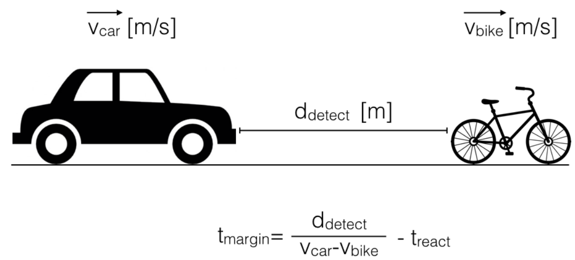

Figure 6. We calculate the system detection time t_{detect} using the relative velocity of the car and bicycle $\vec{v}_{car} - \vec{v}_{bike}$ and by finding the average detection distance d_{detect} of our system. Margin of safety t_{margin} is calculated using $t_{react} = 1.6$ s from Olson and Sivak [34].

TECHNICAL EVALUATION

We perform a technical evaluation to characterize the precision of our system and the margin of safety it provides to users with the cycling application. For test data, we run our system on 8 sample videos from a cyclist's point of view in traffic situations. There are two main classes of these videos: 5 of them have a car approaching roughly 15 mph (24 km/h) relative to the bicycle, the other 3 have vehicles moving the same speed as the bicycle.

We use a pretrained model for our object detector, which has been characterized by its creators to have a Mean Average Precision (mAP) 78.6 [40]. Once objects have been tracked and filtered, they remain detected by the system with a confidence of 89.7% per frame over our training data.

We define the "margin of safety" t_{margin} of our system as the difference in time between when HindSight detects a potentially dangerous vehicle and a baseline reaction time t_{react} to avoid accidents in traffic. We compute t_{margin} by assuming a constant relative velocity between the bicycle and an approaching vehicle $v_{car} - v_{bike}$ and determining the average distance d_{detect} at which HindSight detects objects (Figure 6).

As intended, the cars moving the same speed as the bicycle in the 3 videos are not detected by our system because of the bounding box growth filter. For the remaining 5 videos, we select the first frame where our system detects a dangerous car and visually determine how far from the bicycle the detected car is. To determine the average detection distance d_{detect}, we assume an average car length of 4.7 meters and constant relative velocity $v_{car} - v_{bike}$ of 6.7 m/s (15 mph).

On average, the system detects the car 1.89 seconds ($\sigma =$ 0.40 s) before the car would hit the bicycle. These values were determined by observing the videos and counting the number

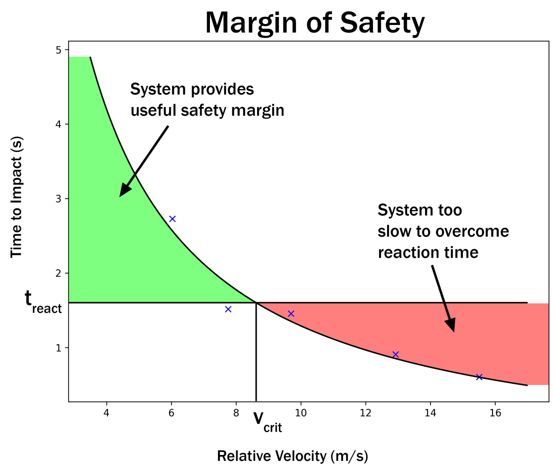

Figure 7. HindSight provides adequate time to react when vehicles approach the user at or under $v_{crit} = 8.62 \pm 1.24$ m/s (green fill, top left), assuming a baseline reaction time of $t_{react} = 1.6$ s. The points × are detection distances measured from system use. The isodistance curve is fitted from the average of the distances.

of frames from the time that the dangerous object is detected to the time it would hit the user.

We determine the margin of safety for our system by plotting detection time values against approximate relative velocity (Figure 7). Relative velocity is calculated by dividing the distance the vehicle needs to travel to hit the bicycle by the amount of time it takes the vehicle to reach that point. An inverse function is fit to these points to generate an isodistance curve that represents the average distance our system detects a dangerous vehicle.

$$t(v) = -0.65 \text{ s} + \frac{19.4 \pm 2.8 \text{ m}}{v \text{ m/s}}$$

Assuming a maximum[1] baseline reaction time t_{crit} of 1.6s to an unexpected roadway obstacle [34], we can determine the maximum speed v_{crit} that a car can be moving relative to the user for our system to provide enough time to react.

$$v_{crit} = v(t_{react}) \qquad = \frac{19.4 \pm 2.8 \text{ m}}{(1.6) + 0.65 \text{ s}} = 8.62 \pm 1.2 \text{ m/s}$$

Therefore, our system can operate safely in situations where nearby vehicles are traveling at most 8.62 m/s (19.28 mph, 31.03 km/h) relative to the bicycle. Assuming an average bicycle speed of 10 mph (16 km/h) means HindSight can currently handle situations where cars travel around 25 mph, a common city speed limit, but that it may need earlier detection to handle speed limits 35 mph (55 km/h) or above.

[1] Olson and Sivak suggest once drivers are *alerted* of an upcoming obstacle beforehand, 95th percentile perception-response time for the same population drops to about 1.1 seconds

EVALUATION

To evaluate the efficacy and usability of HindSight, we conduct two studies in Virtual Reality (VR). While the most externally valid study design would be real-world deployment, using a prototype system in live traffic situations poses serious safety concerns. Instead, we use VR to safely approximate the experience of riding a bicycle in traffic with HindSight, as VR has been used successfully to simulate other high-risk situations [44, 6].

First, we conduct an exploratory evaluation of HindSight by showing participants videos of real traffic situations taken from a cyclist's perspective. Video provides realistic imagery of everyday traffic scenarios, but comes at the cost of participants having no control over the bicycle's movement. In the second study, we perform a controlled user evaluation with a VR game engine, enabling safe simulation of higher-risk traffic situations and allowing participants to control the bicycle.

STUDY 1: EXPLORATORY STUDY WITH VIDEO

To determine whether HindSight's cycling application can increase users' awareness of vehicles approaching in a potentially unsafe way, we first conducted an exploratory evaluation.

To safely emulate the experience of riding a bicycle in light traffic with HindSight, we show participants 360-degree videos recorded from the point of view of a bicyclist via a head-mounted VR display. Videos shown were not stereoscopic. Video data is fed into HindSight to generate sounds from prerecorded objects during trials.

Videos of live traffic situations were recorded by two researchers in a suburban location with minimal vehicular and pedestrian traffic. One researcher rode a bicycle with our system running and capturing 360-degree video, while the other drove a car to simulate various traffic situations. A studio-quality stereo audio recorder was attached to the bicycle to collect environmental sound with approximate spatial cues.

In the evaluation apparatus (Figure 8), a Unity[2] application plays the 360-degree videos and recorded audio back to an Oculus DK2 VR display and in-ear headphones. Users can look around as the video plays using head orientation data from the DK2's IMU. This data is also used in calculations for the HindSight Orientation Filter and for logging metrics for the user evaluation. Audio cues for objects are played through Trekz bone conduction headphones which are positioned in front of the regular headphones on the participants' skull.

A minor technical difference between using our system live and in the simulator is that our 360-degree camera is capable of recording video at 30 Hz, but only capable of streaming video at 15 Hz. We expect this impact on results to be negligible.

Method

Participants were instructed to sit in a kneeling chair to emulate riding a bicycle and were fitted with our evaluation apparatus. Participants were then shown 9 distinct videos. The first, consistent across all trials, was played twice–without and with the HindSight system activated–to familiarize participants with

[2] https://unity3d.com/

Figure 8. Users wear an Oculus DK2 head-mounted display which plays back 360-degree videos and manipulate a joystick to indicate areas with potential danger. Bottom left: users see images of the scene through a "virtual camera"

our experimental apparatus and system. The remaining 8 videos were shown to the participants in random order, and with HindSight randomly enabled for each. This allowed us to obtain a fair distribution of results for each video with a roughly even number of participants trying each video with and without HindSight . All sessions lasted under 30 minutes, and each participant successfully completed the evaluation. One participant's results were omitted due to a technical error which caused their data to not be logged.

During each video, participants were instructed to point a provided joystick towards the area where they considered the most potential danger was in the scene, if it existed. At the end of the evaluation, users were asked to fill out an exit survey. Questions were included open-ended answers and 5-point Likert scales (1 = "Strongly Disagree", 5 = "Strongly Agree"). Likert scale questions were phrased as follows: *(Awareness) The system identified dangerous situations I would NOT have noticed without it, (Comfort) I felt more comfortable when the system was activated, compared to when it was not, (Safety) I felt safer when the system was activated, compared to when it was not, (Stress) I felt LESS stressed when the system was activated, compared to when it was not, (Reaction Time) I had more time to react to situations when the system was activated, compared to when it was not.*

Participants

We recruited 16 participants (11 male, 5 female) using university mailing lists, all graduate students with experience riding a bicycle. 13 participants had ridden a bicycle in traffic, with most participants reporting only occasionally doing so ($\mu = 2.7, \sigma = 1.4$ on a 5-point Likert scale where 1 is "I have never ridden a bicycle in traffic" and 5 is "I commute on a bicycle 5+ times per week").

STUDY 1: PRELIMINARY RESULTS AND DISCUSSION

Increased Perceived Awareness, Safety, and Reaction

In the exit survey, participants generally expressed positive reactions to using our system (Figure 10). Participants reported

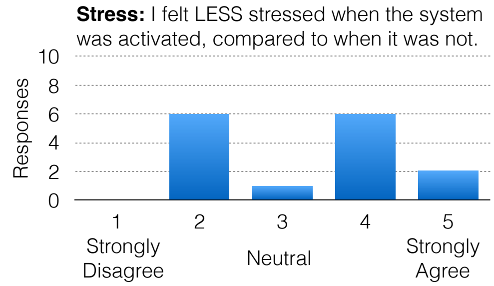

Figure 9. Participants were split on whether HindSight increased or decreased their stress level.

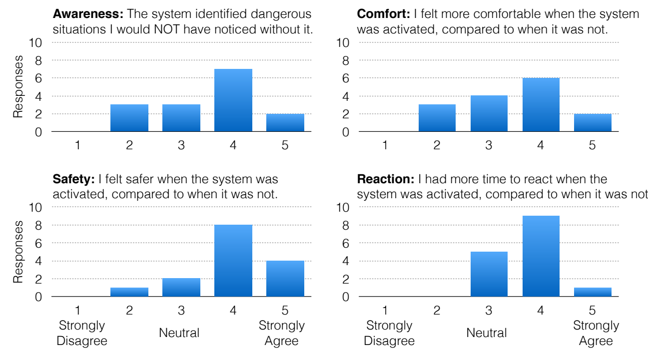

Figure 10. In the exit survey, participants generally gave positive subjective ratings to HindSight on Likert scales asking about awareness, comfort, safety and reaction time.

a perceived increase in awareness, ($\mu = 3.53, \sigma = 0.96$), defined as the ability to identify dangerous situations they otherwise would not have noticed. Some participants explicitly commented on this aspect in open responses: *"It identified passing cars before I could hear them passing by."* (P9); and *"[it did well on] Notifying cyclers of unseen approaching objects, especially if they did not hear/anticipate it."* Participants also reported a perceived increase in time to react ($\mu = 3.73, \sigma = 0.57$), comfort ($\mu = 3.47, \sigma = 0.96$), and safety ($\mu = 4, \sigma = 0.82$) when using HindSight. Full distributions are shown in Figure 10.

Bimodal Response on Perceived Stress

Interestingly, we see a bimodal distribution for perceived stress (Figure 9); for some HindSight increased stress, while for others it decreased their perception of stress. P8, P9, and P12 reported that our system generated some false positives, which may have led to stress: *"Too many false positives. False positives might stress out the user"* (P9). On the other hand, P11 expressed the desire for richer feedback: *"the system gave me a decent view of everything, but I still felt like I wasn't getting the full view even when there was no danger."* More training would let users become more familiar with the system and could eliminate increased stress for some. As P1 notes, (*"I definitely became more accustomed to the system as time went on"*) and P5 remarks (*"My lack of comfort or increased stress with the system might've just been because I'm not used to it. I recognize that it sometimes alerted me to things sooner than I would've noticed them but it also felt a little distracting. I would guess that this would get better with time"*).

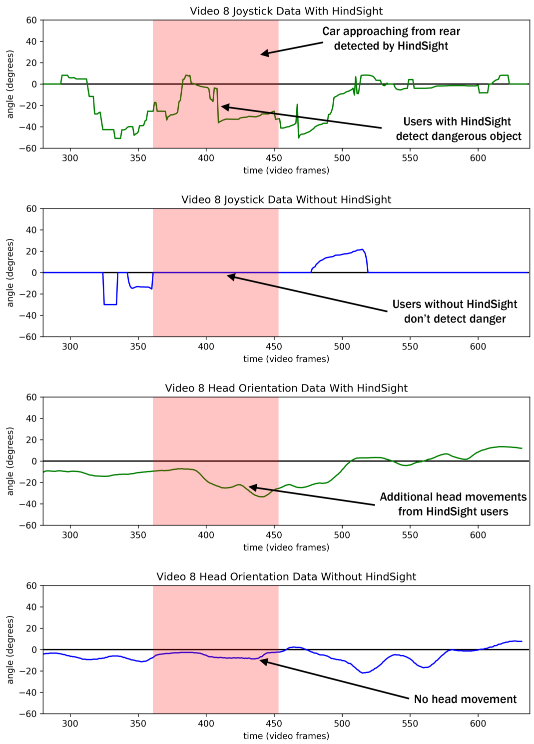

Figure 11. Top two: averaged joystick angle for the "right turn" video for users using and not using HindSight. Bottom two: averaged head orientation for the "right turn" video. The red region shows when an unexpected car appears behind the users. 7 out of 11 participants who used HindSight reacted to the unexpected passing vehicle, while none of 4 who *did not* use HindSight reacted.

Quantitative Results are Inconclusive

Quantitative data from joystick and head movement did not differ significantly between conditions. Using joystick movement as a proxy for when users react to potentially dangerously approaching cars, we found users who viewed videos without our system reacted to a potentially unsafely approaching car in ($\mu = 1.01$ s, $\sigma = 0.48$ s), compared to users who used HindSight ($\mu = 1.04$ s, $\sigma = 0.74$ s). The 30 millisecond average difference corresponds to the duration of a single video frame.

One possible explanation for the inconclusive results is that the interpretations of "potential danger" was too subjective. Some users moved the joystick towards parked cars to mark them as "dangerous", while others did not.

HindSight May Effectively Redirect Attention When Users are Distracted

Although our quantitative results were inconclusive across the set of videos, one datum of interest emerged for a video with a distractor. Near the end of this clip, the bicycle slows down to a stop at an intersection as a truck quickly stops and clears the intersection. In the meantime, a car out of view quickly stops alongside the bicycle from behind. Without HindSight, 0 out of 4 turned towards the approaching car from behind, whereas 7 out of 11 participants using HindSight noticed the car, as determined by head orientation data (Figure 11). This suggests that our system may be especially effective at redirecting user attention when they are distracted by other stimuli.

Feedback for Improving HindSight

Participants also offered suggestions for how they would improve HindSight for use during their real commutes. As is, participants rated the system favorably when asked if they would use it during their real commutes on a 5-point Likert scale ($\mu = 3.87, \sigma = 0.96$). However, comments regarding the audio output and occurrence of false positives suggest avenues for further work.

Explore a Broader Space of Audio Cues

Many users remarked they would like to see revised audio cues: *"I'd want to see some more granularity in the alarm response depending on the seriousness of the danger"* (P11), *"maybe it could use a more distinct effect to denote the severity/distance of the danger"* (P5), *"It could also be a measure of how fast or how big the vehicle approaching is"* (P2). Our current design uses beeps which change in tempo and volume. Investing additional resources in sound experience design could enrich the experience of using our system.

Reduce Incidences of False Detections

Although we designed our filtering stages to reduce our system's false detections, users felt the remaining false positives still impacted usability. *"I heard some false positives from parked cars receeding away from the bicycle"* (P12), *"Sometimes does send misleading beeps (got a few when no car was immediately approaching)"* (P7). Additional signal processing will be needed to further reduce the number of false positives. One proposal for future work is to incorporate the *trajectory* of approaching objects with a dynamics model.

STUDY 2: EVALUATION IN SIMULATED TRAFFIC

To determine how participants would react to HindSight while navigating higher-risk traffic situations, we conduct a controlled user evaluation of HindSight in a simulated traffic environment in VR.

Using a VR-based simulation of various traffic scenarios, as opposed to viewing videos in a VR headset, has several critical advantages. First, a simulator gives participants agency over the bicycle's movement, enabling them to react to vehicles realistically rather than using a joystick as a proxy to indicate dangerously approaching vehicles. Using simulation also enables safe testing of higher-risk scenarios, such as a difficult-to-avoid collision with an approaching vehicle. In this section, we describe the implementation and use of a VR-based simulator, to conduct a controlled user study of HindSight.

Simulator Design Considerations

For our simulator to be an effective platform to study HindSight, it must accurately emulate use of HindSight in various scenarios, being both realistic and comfortable for participants to use. Its design was guided by the following principles:

Provide sufficient realism and immersion: The simulator must emulate cycling in traffic realistically for participants' interaction with HindSight to be representative of real-world use. This is expected to result in more representative reactions to other vehicles due to a more realistic sense of *risk*, e.g., because it is safe to simulate a collision between the participant and an approaching vehicle in VR.

Enable development of repeatable scenarios: The simulator must support the creation, playback, and logging of multiple scenarios to validate the use of HindSight in a variety of traffic situations. Each scenario consists of a section of geographical area, actions for vehicles to take contingent on the participant's location, and markers to direct participants through the course. Scenarios are used to encode traffic situations with varying levels of distraction and collision risk.

Reduce simulator sickness as much as possible: For some, use of VR HMDs causes "simulator sickness", or "cybersickness", which has symptoms similar to motion sickness [24]. Although the exact causes are not entirely clear [39], several design principles have been documented to mitigate symptoms, such as reducing forward movement speed [39], avoiding tasks which require significant angular rotation [24], and limiting the duration inside VR [9]. In our simulator, we limit the forward speed of the bicycle to roughly 10 mph, choose a straight course through the map to eliminate turns, and set a target duration of the time in VR to be under 10 minutes.

Apparatus

We choose Grand Theft Auto V (GTA)[3] as a platform for our traffic simulator because of the realism of its driving environments and its use in autonomous vehicle research [26]. Adapting GTA to a simulator for evaluating HindSight was a significant engineering challenge: GTA does not natively support modification (e.g., control of in-game entities) nor Virtual Reality displays.

Scenario Scripting

Although GTA does not natively support modification, a community of users has reverse engineered its game engine by mapping memory addresses to in-game functions. We used ScriptHook.Net, an API wrapper of these mappings, to create our simulator. This enables us to control in-game properties (e.g., where vehicles or pedestrians spawn, if needed) and tie into game engine event hooks. Another tool developed by the community is OpenIV, which allows one to modify various asset files in the game engine. We used OpenIV to change the speed of the in-game bicycle and vehicles to fixed speeds, enabling precise control of timing for scenarios.

To test the capabilities of HindSight in various scenarios, we need the ability to precisely script events that respond to a user's actions and location in GTA. To achieve this, we develop a JSON-based description language for scenarios which can be parsed by the simulator. These scenario description files include specifications for the environment (the in-game time of day, whether or not time should pass, etc.); placement of in-game entities (where to spawn the player, pickup items, other vehicles, trigger planes, etc.); and actions to associate with in-game entities (what routes spawned vehicles should follow, and at what speeds; events to trigger when the player crosses a trigger plane, such as calling script functions; etc.). As the user progresses through scenarios, they cross trigger planes that intersect their path, spawning vehicles that follow scripted paths at set speeds. If the user is in the way of the vehicle as it travels along its path, a collision will occur. To edit and debug scenarios, we develop an in-game authoring tool (Figure 12) which allows placing in-game objects, vehicles, and waypoints; and visualizes this data in-engine.

[3] https://www.rockstargames.com/V/

Figure 12. Screenshot of in-game scenario editor: red lines represent vehicle trajectories, gray planes trigger actions when crossed, and blue blobs cover obstacles (e.g., parked cars).

To analyze the events that occur during our user studies, we built a system to log in game events, locations of vehicles, and user inputs to a csv file. All of the data gathered for these log files were captured from the game engine using ScriptHook.

Using GTA with Virtual Reality

GTA does not natively support VR displays. As a workaround, we use a program called VorpX[4], which captures scenes generated in DirectX game engines and routes them to a supported VR headset. Rather than the Oculus DK2 used in the exploratory evaluation, we use an HTC Vive headset[5] for the simulator because it is recommended for use with VorpX. We opted not to use VorpX's 3D reconstruction algorithm because it significantly reduced the framerate of GTA.

Users control their movement within our simulator using an Xbox One wireless controller[6]. There are considerable issues with remapping user inputs when using the VorpX software. To mitigate this, we built an input processing module using AutoHotKey which captures the inputs from the controller before VorpX and generates a set of outputs that are sent to the game engine but do not interfere with VorpX's controller remapping.

Bridging GTA with HindSight

Due to the modular nature of HindSight, we were able to easily adapt it to generate output for vehicles in GTA. Part

[4] https://www.vorpx.com/

[5] https://www.vive.com/us/product/vive-virtual-reality-system/

[6] https://www.xbox.com/en-US/xbox-one/accessories/controllers/xbox-wireless-controller

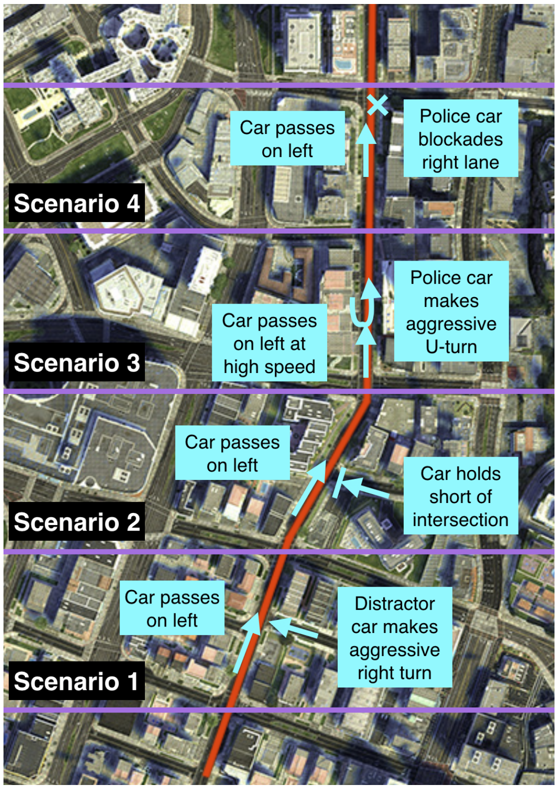

Figure 13. Participants in the simulator-based study followed an urban course in GTA along the red line indicated. The course was chosen to be as straight as possible, minimizing turns to reduce simulator sickness. The course is divided into four intervals where different scenarios take place with HindSight toggled on or off.

of the original HindSight system is a Python program that receives output from the neural network, applying filters and choosing which objects to sonify. Our simulator outputs data to this Python program so that it can generate the correct sound events. In contrast to HindSight, the exact relative positions of each car in the scenarios are always known. For our study, we choose to emit each tracked car position to the HindSight module once it is within our maximum detection distance, approximately 100 feet (30.5 m).

To hear both the environmental sounds generated by the GTA game engine and the audio generated by HindSight through bone conduction headphones, our computer must support simultaneous, low-latency audio streams. The default Windows 10 audio driver allows only one device to take control of the Audio Streaming Input/Ouput (ASIO) interface at a time. GTA is built in DirectX, and by default will use the only available ASIO device. HindSight uses professional digital audio workstation software to generate sounds, which requires an additional ASIO interface. To overcome this limitation, we use a dedicated hardware device with its own ASIO driver, a FocusRite Scarlett 18i20 USB audio interface[7], to output sounds to our bone conduction headphones through a Bluetooth audio adapter.

[7]https://focusrite.com/usb-audio-interface/scarlett/scarlett-18i20

Method

Participants were first instructed to fill out a short survey describing their experience with VR and cycling in traffic. A researcher next explained the interface of HindSight and played example audio cues to the user. Participants were then informed of the general rules of each scenario (described below) and subsequently fitted with the evaluation apparatus. After completing the simulation scenarios, participants filled out an exit survey. All sessions lasted under 25 minutes. 21 participants successfully completed the evaluation.

Participants were instructed to control the bicycle in simulation as if they were cycling in real traffic, with the following exceptions:

- If the bicycle touches any car, their character will instantly "lose a life" and respawn at the beginning of the following scenario.
- Traffic lights should be disregarded[8], and the cyclist may proceed through every intersection with caution.
- Money bags[9] will line the road, indicating the direction of the course. There is no reward for collecting them (by cycling over them) nor penalty for missing any.
- Participants were instructed to complete the course quickly and efficiently, but to always prioritize safety.

Having entered the simulator, we first place users in a training scenario in a desert location to increase familiarity with HindSight. Throughout the training scenario, four cars slowly and safely pass the bicycle on the left, each emitting audio cues from HindSight. During one instance, another vehicle (distractor) quickly comes to a stop at an intersection in front of the bicycle and drives away before it can be reached, posing no real risk of collision. Participants were allowed to repeat the training scenario as many times as they like. All participants completed the training scenario only once.

Following the training scenario, we place users in four scenarios in an urban environment (Figure 13). Each participant completed all scenarios, and participants were alternately assigned to conditions where HindSight was activated only for scenarios 1 and 2, or scenarios 3 and 4, respectively. The scenarios (Figure 14) are scripted as follows, each designed to incorporate a level of "danger" (the risk of collision if no action is taken) and "distraction" (an entity actively redirecting the participant's attention from the danger):

1. **High Danger, High Distraction.** A car aggressively enters an intersection in front of the bicycle from the right (distractor; Figure 14.1a) as another vehicle quickly approaches and passes the bicycle on the left (posing danger; Figure 14.1b). The participant must slow the bicycle to wait for the aggressive vehicle and steer clear of the approaching vehicle to avoid a collision.

[8]Scripthook provides limited control over traffic light entities. As a workaround, we change all lights to green, which may be noticeable to the observant participant.

[9]This is GTA, after all.

Figure 14. Screenshots of key events for each scenario. Numbers superimposed on images correspond to scenario numbers. For each scenario, letters 'a' and 'b' correspond to distractors and passing vehicles, respectively.

2. **Low Danger, Low Distraction.** A car ahead stops at an intersection to wait for the cyclist (Figure 14.2a) while another car slowly passes the bicycle from the left (Figure 14.2b). The participant must remain clear of the approaching vehicle (maintaining the course) to avoid a collision.

3. **High Danger, Low Distraction.** A sports car speeds by the bicycle on the left (distractor; (Figure 14.3a) while a parked police car makes a dangerous U-turn in the path of the bicycle to pursue the sports car (posing danger; Figure 14.3b). The participant must first avoid the approaching car (maintaining the course), then slow for the police car, or swerve to avoid it, in order to avoid a collision.

4. **Low Danger, High Distraction.** The sports car in scenario 3, having collided with a tree, blocks the right lane along with the police car (distractor; Figure 14.4a) while another car slowly passes the bicycle from the left (Figure 14.4b). The participant must steer to the right and wait for the passing car to avoid a collision.

The training scenario takes a minimum of 2.5 minutes to complete, and all the remaining scenarios may be completed in a minimum of 3 minutes.

Scenario	Collisions (HindSight Off)	Collisions (HindSight On)
1	3	2
2	0	0
3	3	0
4	1	0
Totals	**7**	**2**

Table 1. Participants collided with a vehicle 7 times with HindSight deactivated, whereas only 2 collided with HindSight activated.

Participants

We recruited 21 participants (14 male, 7 female) using university mailing lists, all either undergraduates, graduate students, or university staff. All participants had experience riding a bicycle. One additional participant canceled participation early (after completing the training scenario) due to simulator sickess, and their data was discarded. 20 participants had ridden a bicycle in traffic, with most participants regularly doing so ($\mu = 3.57, \sigma = 1.28$ on a 5-point Likert scale where 1 is "I have never ridden a bicycle in traffic" and 5 is "I regularly commute on a bicycle"). 19 participants had used a VR headset before, with 5 reporting having ever experienced simulator sickness.

STUDY 2: RESULTS AND DISCUSSION

Users Crashed Fewer Times with HindSight Activated

Across all scenarios, participants collided with vehicles fewer times with HindSight activated: 7 times with HindSight deactivated compared to only 2 activated (Table 1). Scenarios 1 and 3 experienced the most collisions, which is to be expected as they were designed to be the most dangerous. With McNemar's exact test, we find this result is not quite statistically significant ($p = 0.0625$).

However, it is worth noting the two participants (P14, P18) who collided with HindSight activated in scenario 1 each collided *again* with HindSight deactivated (both in scenario 3). One possible explanation was that these users did not feel a convincing sense of risk as they may have on a real bicycle (i.e., two crashes as such would be unlikely).

HindSight Led to Increased Distances to Vehicles

In addition to reducing collisions, we found participants cycling through scenarios with HindSight activated maintained greater minimum distances to cars, than in scenarios with HindSight deactivated (Figure 15). A potential explanation for the high variance of this result may be due to *risk compensation* (i.e., participants may feel more comfortable taking greater risk with the added output of HindSight) [54]. Nonetheless, we consider an average increase of minimum distance to be a positive result.

Impact on Head Movement is Unclear

The temporal relationship between head movement about the yaw axis and the time when a user is nearest a passing vehicle could indicate early awareness of the vehicle (e.g., if the participant turns their head to acknowledge the passing car). This pattern emerges in scenario 1 (Figure 16), where many

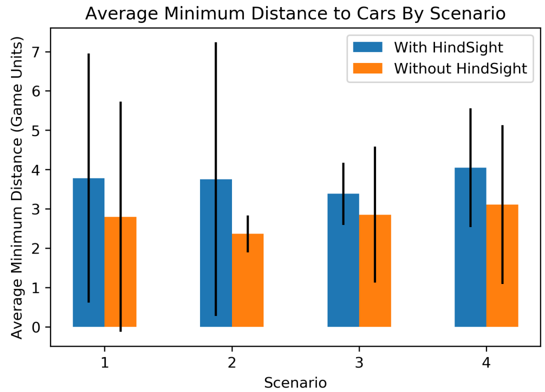

Figure 15. Participants with HindSight enabled left more distance between themselves and other vehicles than with HindSight disabled, on average, across all scenarios. GTA distance units are roughly equivalent to feet. Error bars reflect standard deviation.

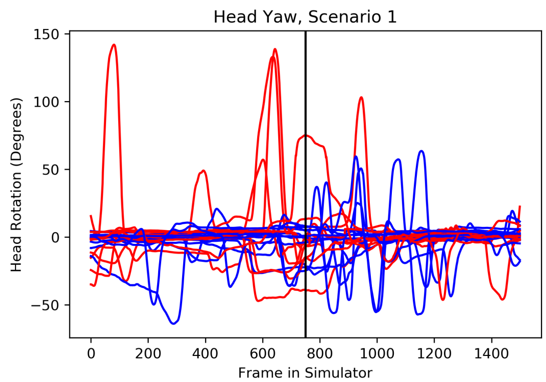

Figure 16. In scenario 1, participants using HindSight (red lines) tended to turn their heads to look to the left before their closest distance to car in the scene (black vertical line). Participants with HindSight deactivated tended to turn their heads afterwards (blue lines). There was no clear relationship in any other scenario.

users with HindSight activated turned their heads to the rear left about 100 frames (approximately 3 seconds) before the passing vehicle was nearest them, whereas participants with HindSight deactivated tended to turn their heads afterwards. There was no clear pattern in other scenarios.

Another important relationship between HindSight and head movement is the magnitude of head movement in each scenario (Figure 17). We use the total area under the head yaw curve for each scenario to measure this. We found participants made slightly fewer head movements in all scenarios with the exception of scenario 1. A potential effect of HindSight could be to *increase* the amount of rotation as users turn their heads to acknowledge more approaching vehicles, while, in contrast, it could very well *decrease* rotation as users become more accustomed to (or dependent on) HindSight's output. Identifying richer metrics and investigating these results through qualitative study would be an important topic for future work.

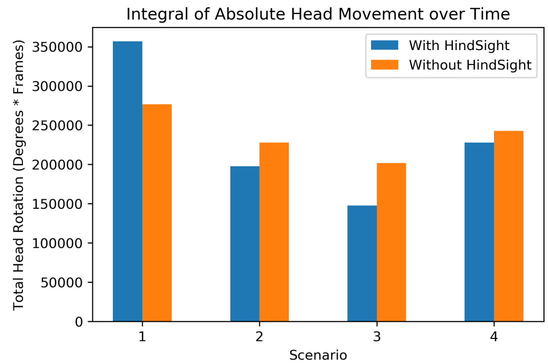

Figure 17. With the exception of scenario 1, participants had marginally reduced head movement with HindSight activated.

HindSight Perceived to Help Avoid Collisions, Identify Cars, and Identify Dangerous Situations

In the exit survey, 14 participants (66.7%) responded that HindSight helped them avoid a collision. 19 participants (90.5%) responded "Yes" to *"The system identified cars and obstacles BEFORE I would have noticed them"* and 17 (81%) responded "Yes" to *"The system identified dangerous situations BEFORE I would have noticed them."* These responses suggest HindSight effectively increases the perceived environmental awareness of participants.

Reduced Cognitive Load

As part of the exit survey, participants filled out NASA TLX workload assessments (with the "Physical Demand" question omitted) for scenarios with and without HindSight activated, and Raw TLX scores were used to calculate cognitive load [14]. On average, participants' cognitive workload was lower when HindSight was activated ($\mu = 0.42,\ \sigma = 0.11$) compared to when it was not ($\mu = 0.53,\ \sigma = 0.12$)—a 21% reduction. This result suggests that, while participants performed better with HindSight (fewer collisions), they also expended less effort.

Increased Perceived Safety and Reaction Time

Participants generally echoed the positive reactions expressed in the exploratory evaluation, reporting increased subjective ratings of safety ($\mu = 4.10,\ \sigma = 0.70$), reaction time ($\mu = 4.05,\ \sigma = 0.74$), and comfort ($\mu = 3.67,\ \sigma = 0.97$) while using (Figure 18).

Reduced Stress in Most Users

To further understand the bimodal response to stress in the exploratory study, we separately asked users if HindSight increased and decreased stress (Figure 18). Most users felt HindSight decreased their stress ($\mu = 3.43,\ \sigma = 0.93$), and few felt HindSight increased their stress ($\mu = 2.38,\ \sigma = 1.12$).

We asked participants to elaborate on their response to the questions about stress. Currently, the beeps increase in frequency and pitch as a vehicle approaches, a possible contributor to stress: *"I also didn't like how fast the tones clicked when the vehicles was super close, as it made me too anxious"* (P6). False positives also contribute to stress: *"Sometimes I would hear the beep, but turn and not see a car, which was freaky"* (P19).

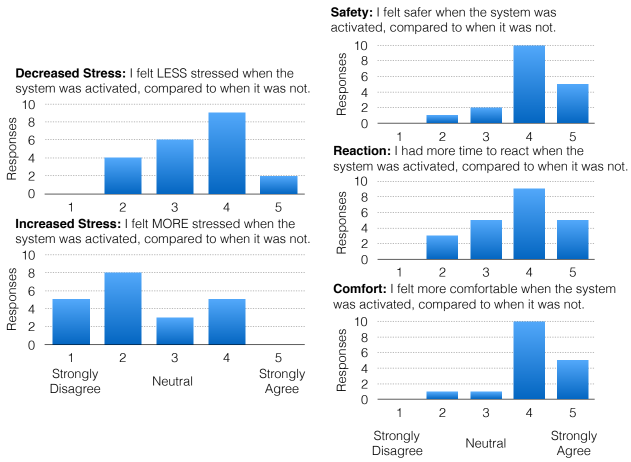

Figure 18. Participants generally gave positive ratings to HindSight on Likert scales asking about safety, reaction time, and comfort. Most participants felt less stress while using HindSight, while few felt increased stress.

Some participants remarked that using HindSight was stressful, but completing scenarios without HindSight was even more so: *"The beeps made me feel stressed because it implied a potential collision, but I felt much more stressed once the beeps were turned off entirely."* (P14); *"I wasn't sure of how well the system works, but having the system off was definitely more stressful"* (P5). Other participants describe how the increased awareness from HindSight reduced stress: *"I like knowing when cars were behind me with the beeps rather than having to look behind me or listen for engines"* (P7); *"I was less stressed as I didn't need to actively search"* (P10); *"Having the system gave me a sense of safety"* (P17).

Open-Ended Feedback

We asked participants to provide open-ended comments on what the system performed well on, what needed to improve, and what would need to be changed to make it ready for a real commute. We conducted an open coding phase over the qualitative responses, and further grouped codes into related topics [53].

Awareness of Vehicles Approaching from Behind

Many participants commented on the effectiveness of HindSight increasing their awareness of their surroundings. *"It did a good job making me aware of cars coming from behind"* (P2); *"I think the system successfully made me aware of the cars behind me"* (P3); *"[HindSight did well on] Noticing the cars behind well before I did"* (P13). P9 goes as far as to say *"This system is really nice in detecting when things were coming up behind me, so much that I felt more threatened by how the cars would act in front of me."*

A few participants used the metaphor of an "added sense" to describe how they felt, speaking to our original design goal of overcoming sensory limitations. P8 remarks, *"the system helped me feel like I had another sense: it was more difficult (probably because I'm not used to it), but I felt much more in tune with my surroundings,"* as well as P6 who notes, *"It gave me the extra set of eyes."*

Inferring Vehicle Intent from Audio

Participants expressed differing opinions on the design of audio cues. P8 notes *"the sounds are gentle, non-distracting, and easily interpretable."* One area of disagreement among responses was HindSight's ability to convey the actions of vehicles behind the user. Some users were easily able to discern the tracked vehicle's distance: *"the frequency of the beam made me aware how far is the car toward me"* (P3); *"it was pretty spot on for detecting the nearness of cars"* (P19); *"The beeps always came in a specific pattern so I was able to expect exactly when the car would come up to me"* (P17).

However, other participants had the opposite experience: *"I did not have a good way of judging how far away the car was"* (P9); *"It would be good to get a better sense of how fast and how close they are, rather than a car is approaching generally"* (P18). Some participants noted a better mapping for the rate of beeps may be an estimated time to pass: *"The beeps didn't do a good job of telling me exactly how much time I had before a car passed me"* (P2); *"Have the beeps start/end based on the time a car is away from you, rather than physical distance"* (P10). Exploring this alternative mapping would be a valuable component of future work.

Localization with Bone Conduction has Variable Results

Several participants commented that distinguishing the direction of an approaching vehicle was challenging: *"I couldn't necessarily determine the direction of the cars (which side of the road)"* (P7); *"I'm not confident that I would be able to distinguish between a beep on the left vs a beep on the right."* (P10). Other participants voiced similar usability hurdles (P6, P8, P11, P15, P19). A potential cause for difficulty in localizing beeps is the linear mapping of the angle of the approaching vehicle to stereo pan. Future work could consider different mappings (e.g., logarithmic) to accentuate the direction of a vehicle approaching from far behind. Another potential cause is the high transmission variability of bone conduction headphones—their response is strongly affected by their positioning on the user. Although participants were instructed to first adjust the headphones until they could clearly differentiate beeps coming from the left and right, it is possible the headphones moved before or during simulation.

Exploring Different Output Modalities

Some participants remarked they preferred the vibration of the bone conduction headphones to the higher-frequency audio: *"Maybe less beeps, and more vibration"* (P18); *"the vibrations of the system helped more than the noise"* (P21); *"We can try some other means rather than sound. Maybe just vibrations"* (P13). On the contrary, P6 comments, *"The high pitch is good since it can be heard above ambiance."* Overall, this suggests an exciting direction for future work may involve comparing the effectiveness of different output modalities for use with HindSight.

Handling Output in Heavy Traffic

A few participants expressed concern that continuous beeping in heavy traffic would be overwhelming: *"I can imagine the* *system can be constantly beeping if I use it [during rush hour]"* (P20); *"for a real commute there are more than just one car on the road [...] too many sounds many be confusing to the user and overpowering"* (P4). P8 expressed the opposite desire: *"I think I"d rather have the beeps around me all the time!"* HindSight limits its output to sonifying a maximum of two objects, but added features, such as thresholding for minimum differential speeds, could be mitigation strategies in future work. Another solution may be interactivity. P6 suggests, *"It would be nice to have some way for the user to acknowledge vehicles they have already seen."*

LIMITATIONS

As a prototype system, HindSight has limitations from engineering constraints and the availability of technology.

The resolution of our panoramic camera is relatively low. Output is at 1280x720 at 15 fps streamed live. A rough calculation shows using a 4K panoramic camera could provide twice the detection distance of our 720p camera, increasing users' limited time to react.

Our system requires a 10 lb laptop to be worn. Our laptop was chosen as a solution to balance portability and a high-end GPU. Although it can be comfortably worn in a backpack, it is not an ideal form factor. Developments in low-power, small-footprint hardware designed for neural network computations[10] and considering mobile-optimized neural network architectures [16] will likely address this limitation.

The Orientation Filter can reduce sensitivity to objects approaching from directly behind. The Orientation Filter works effectively in practice because cars commonly approach the bicycle at an offset from the rear. However, objects which are approaching directly from behind may be detected later because their tracked x value does not change. Engineering a dynamics model which estimates the *trajectory* of directly approaching objects could resolve this limitation.

Object tracking does not merge bounding boxes. Our frame to frame tracking algorithm could be improved by adding a step where we merge bounding boxes if items are likely the same at seams of image partitions.

CONCLUSION

We introduced HindSight, a wearable system that increases spatial awareness by detecting relevant objects in live, egocentric 360-degree video and sonifying their attributes through bone conduction headphones. HindSight draws upon advances in computer vision and work in delivering continuous feedback for physical tasks to identify points of interest in a user's surroundings and notify the user when necessary to redirect their attention.

Our analysis suggests that at current detection performance, bicyclists can be notified in time to react to dangers when vehicles travel up 8.6 m/s faster than the cyclists. This margin may be sufficient for many, but not all urban cycling situations. Progress in camera technology and object classification can further improve on this threshold.

[10]https://developer.movidius.com/

In our exploratory study, we find HindSight increased users' reported comfort, awareness, reaction time, and safety. We also identified potential avenues for future work, such as reducing the recall rate of object detection and designing broader audio experiences for users.

In our simulator-based user study, we find participants using HindSight experienced fewer collisions, increased their distance to other vehicles, and had reduced cognitive load. Participants expressed increases in reported awareness, safety, reaction time, and comfort similar to the exploratory study.

While our prototype is somewhat limited by the need to wear a laptop with a powerful GPU, multiple companies have developed chips that can run deep neural networks in real time, which would make a truly portable solution feasible.

Beyond the domain of cycling, we believe that combining an enhanced awareness of visual periphery with the rich semantic understanding of objects and scenes from computer vision techniques has the potential to enable an entire new class of applications that improve on unaided human capabilities. Ultimately, we believe HindSight represents a step towards such systems which can increase our potential by facilitating human-machine collaboration.

ACKNOWLEDGMENTS

This work was supported in part by the VeHICaL project (NSF grant #1545126) and by TerraSwarm, one of six centers of STARnet, a Semiconductor Research Corporation program sponsored by MARCO and DARPA.

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