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Enhancing Driver Awareness Using See-Through Technology

Rebekah L. Thompson, Zhen HU, Jin Cho, Jose Stovall, and Mina Sartipi University of Tennessee at Chattanooga

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Abstract

This paper presents a real-time application of see-through technology using computer vision (e.g., object detection) and Vehicle-to-X (V2X) communication (e.g., Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I)). Each access point (AP) was connected to Chattanooga's fiber optics internet, supporting a data transfer rate up to 10-Gbps. Using a 5Ghz frequency, vehicular communications were set up with a seamless handover for transferring real-time data. Two web cameras acting as clients were mounted on the windshield of two of three vehicles to send image data to the offsite server. Using multi-threaded programming, both image feeds were processed simultaneously. Once the server received the images, it performed an object recognition algorithm on each image using a convolutional neural network (CNN). Post- identification, the images from the second vehicle were sent and overlaid dynamically to the third vehicle's image. This repetitive overlapping of images allowed the third vehicle to "see-through" the second vehicle in real-time. This experiment was showcased during the US Ignite Smart Cities Summit in June 2017 to emphasize the benefits of drivers being able to "see-through" the car in front to make more intelligent decisions when passing a vehicle, stopping for a pedestrian, or seeing an upcoming detour due to construction before the view is within their line of sight. Using V2X communication with computer vision gives the driver a higher level of awareness and allows better decision making in the case of a roadway conflict, ultimately increasing the level of safety on our roadways.

Introduction

From calls, texts, e-mails, and even mobile games, distracted driving is prevalent on roadways today. One of the most simple solutions to decrease distracted driving and increase driver awareness would be to stop using mobile phones while driving, but in reality, a request such as this seems highly unlikely. In 2015, the National Highway Traffic Safety Administration's National Center for Statistics and Analysis published a report of statistical analysis related to distracted driving [1]. It was reported that of the 32,166 vehicle crashes that occurred, 3,196 (10%) were distraction-affected. Of those 3,196 distracted-based crashes, 442 were documented due to the use of mobile phones. The same document also reports that of the 35,092 fatalities reported, 3,477 (10%) were distraction-affected and 476 were documented due to the use of mobile phones.

According to the Centers of Disease Control and Prevention [2], there are three categories of distracted driving: visual, manual, and cognitive. Visual distractions occur during an event where the driver takes their eyes off of the road, manual distractions occur when the driver takes their hand(s) off of the steering wheel, and cognitive distractions when the driver takes their mind off of the actions taking place on the roadway around them. Any one of these distractions can increase the potential for an incident and combining more than one can increase the rate even more. A recent campaign to raise awareness and attempt to decrease distracted driving is the "It Can Wait" campaign commissioned by AT&T [3]. To date, the campaign has had approximately 21 million pledges to stop using smartphones while driving. Another campaign created by the Ad Council and National Highway Traffic and Safety Administration (NHTSA) is "Stop Texts. Stop Wrecks." [4]. As the name states, the main purpose of this campaign is used to promote awareness of the dangers of texting and driving. In relation to the three types of distracted driving listed above, texting is one of the most dangerous because it combines all three of the distracted driving categories. Thinking about the process of texting and driving, the driver takes their eyes off the road and hand off the steering wheel to access the text and begins using their thought process to perform these tasks plus the action of reading and trying to comprehend the message. The texting example combined each of the three driving distraction categories into the 1-2 second of reading the text; it did not include the extra time it would take for the driver to respond to the text. The time taken to send a text may sound brief, but include the time a driver must process their environment once again post-text. Triggs and Harris [6] tested the reaction times of drivers in different simulations. According to their findings of the 85th percentile reaction time values, the range of driver reaction times were between 1.26 and 3.6 seconds, varying with the type of simulation. Combining the time used to perform a simple task such as texting with a value from the range of reaction times concluded by Triggs and Harris, the driver could potentially be distracted from their driving environment for at least three to ten seconds. On roadways, this that time could result in a collision that could potentially injure the driver or others.

Until the time comes when fatalities from distracted driving can be completely eliminated, solutions must be found to help lessen the risks. Imagine if there was a way to have an extra two to three seconds added to the time between a driver being made aware of an obstacle and having that extra time to react to the situation. The driver may be able to think more clearly about what actions to take to avoid or prepare for the obstacle; this can also create a buffer between a distracted driver and the real-time action they need to take pertaining to the obstacle ahead. One such way to give the driver a larger time span to react to an obstacle is by using see-through technology.

See-through is the process of overlapping and stitching, or combining, images from one or more cameras onto one or more related images from another camera by transferring the images through V2X communication. V2X communication currently includes V2V and V2I. Previous research has been done using see-through techniques and V2X communication to create an augmented view to broaden the field of view for drivers behind other vehicles [25, 26, 27].

In this paper, the concept of see-through technology using V2X communication is explored in the context of improving driver awareness. Two experiments are conducted using V2X communication; one with the use of V2I and V2V communication and one with only V2V communication. The next section will provide a brief background of the concept of computer vision and object detection to better understand the core assets to the algorithm used in each experiment and provide a clearer understanding of the methods used during the experiments. The Methodology section will introduce and describe the methods used for each of the two experiments conducted. The results section will analyze results from each of the experiments separately. Following the Results section, the paper will discuss the results from the two experiments as a whole. This paper will conclude with a summary of steps taken to come to explain why see-through technology is beneficial to drivers by raising their awareness in a real-world driving environment.

Background

Computer Vision

Computer vision is the process of interpreting and extracting information from a still image or video feed to achieve a particular goal. Just as humans use their eyes to obtain information from the world around them, computers can obtain information with the use of a camera and an algorithm. The algorithm is designed to process the image in the particular way needed to extract the necessary information to achieve the user's goal [7]. Unfortunately, the computer does not see the objects in an image as separate object forms. Instead, the image is converted to greyscale, analyzed, and converted back to a red, blue, and green (RGB) image. During the greyscale period, the computer sees the individual pixels that make up the image that range from 0 to 255 depending on the brightness of the pixel (see Figure 1). These values are used as building blocks for the computer to compare different sections of an image to find similarities between the input image and the image data stored in its database. By doing this, the computer can form a recognizable image comparable to the image we see as humans. This is the basis of how we are using computer vision as a primary tool for see-through. By using the information gained by the computer vision process, individuals can create algorithms to train the machine to recognize and identify an object, also known as object detection or object recognition, within an image [8, 9, 10, 11, 12]. Example of this identification are shown in Figures 2 and 3.

FIGURE 1 An excerpt of a pixel matrix created by the analysis of a section of an image. The values range from 0 to 255 depending on the brightness of the pixel during the greyscale analysis phase.

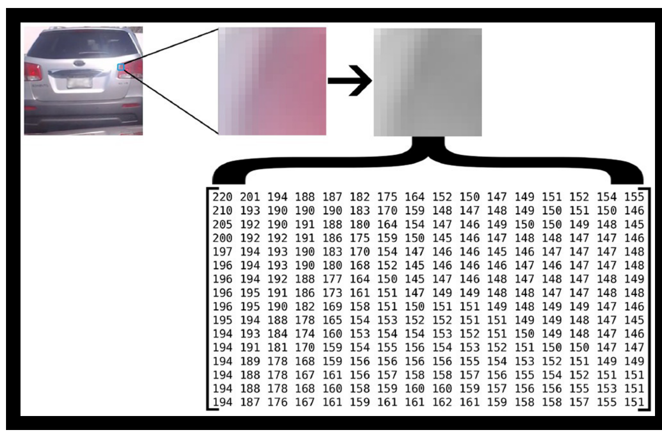


FIGURE 2 Example of object detection and recognition using computer vision and a CNN.

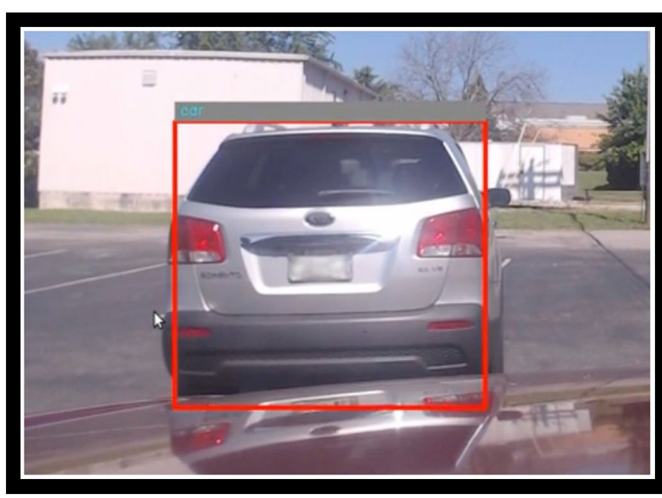
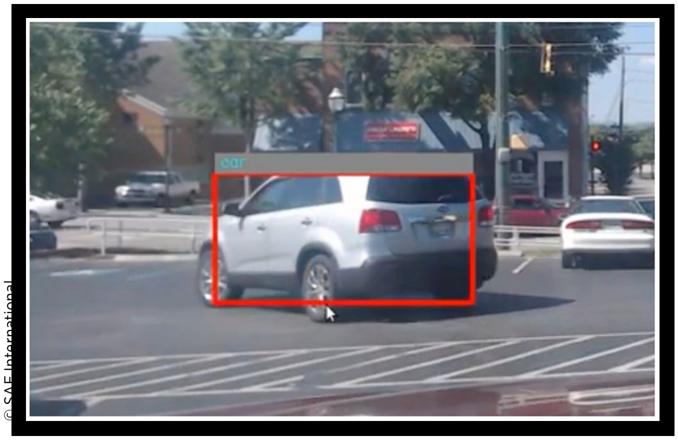


FIGURE 3 Example of object detection and recognition using computer vision and a CNN (side view).



Object Recognition

Object recognition is the process of identifying images with the use of pattern recognition and matching algorithms based on unique features in an image or video [13]. A few feature-based matching algorithms include: histogram of oriented gradients (HOG) [14], Haar cascades [15], and canny edge detection [16]. A different approach that uses more of a deep learning technique is the use of CNNs.

CNNs are used as a more automatic feature recognition in comparison to the previously mentioned feature-based techniques. CNNs are trained by using hundreds to thousands of images that are input into an algorithm to find the primary object in the foreground of the image. When entering the photos, images containing the object and images not containing the object are entered into the algorithm so it learns to recognize the object in the foreground apart from the natural scene of the background. When the image containing the object is entered, it is entered with a label created by a human telling the computer what the object is. Once the network is trained with hundreds to thousands of labeled images, a test image can be put through the network to test the accuracy of the model.

When the image enters the CNN algorithm, the image appears to the computer as a 2D matrix if the image is in greyscale or a 3D matrix if the image uses RGB channels. In the previous section on computer vision, Figure 1 shows an example of a 2D matrix because the image used was converted to greyscale before it was returned as a RGB image. At the beginning of the identification process, the algorithm will scan through the image section by section and learn key features of the image based on the distinct features of the object, such as edges. Due to the images in the database, the algorithm will be able to distinguish the key features of the key object from the background based on the value of the pixels in the matrix. When separating the interpretation of the foreground and background, the background will have a lower pixel value, if not a value of zero, and the foreground that contains a recognized image from its database will have a higher pixel value based on the intensity of the grey or RGB value depending on the type of color channel used. At the end of this algorithm, the features of the object will be determined by the largest numbers of pixel values in the matrix. The algorithm will then create probabilities based on the key features from the test image and the images containing an object and label in the database to determine which object label matches the input image the most. The one that has the highest probability will be selected and output as what item is detected in the image [17, 18, 19, 28].

For a more human-relatable example of the process of a CNN, consider the following idea of a bedroom. In the minds of many, a bedroom normally consists of a bed, chest of drawers, a mirror, a door, and possibly a desk. Now, consider a scenario where someone is in a dark room with only a flashlight. The person has no idea where they are, but they know the layout of their home and can recognize certain objects to identify their location. Using the light from the flashlight, they shine the light from side to side in front of them to see different features of the room. In one section they see a desk, in the next a chest of drawers, and so on. Even though the light can only shine on a small section, the person is able to recognize and store the features of the room they had seen and identified in a previous section to piece each scene together and understand where they are. A CNN works in a similar way, but using more mathematical values and a database of stored images, similar to the human brain storing images to identify objects or scenery at a later date.

Figures 2 and 3 show an example of CNNs in action. Figure 2 displays the CNN's ability to identify a vehicle from the rear, which will be the point-of-view primarily used during the identification process, using a mounted camera on a vehicle's windshield. Figure 3 displays the CNN's ability to identify a vehicle from the side. This viewpoint allows the algorithm to continue while the vehicles are making a turn. If the vehicle in front make a turn while the driver continues straight or the front vehicle moves out of the camera's view, the algorithm will simply redirect its focus onto the next vehicle matching the parameters of the see-through algorithm.

Figures 2 and 3 show the identification process, one of the key components contributing to the see-through process. The bounding box placed around the vehicle displays a rough parameter surrounding the vehicle and gives the coordinates to use when placing the overlapping camera images, which will be discussed further in the next section. The bounding box also plays a role visually by giving the driver a specific place on the video to focus and find the necessary information instead of overloading their brain by scanning the image to find where they need to focus.

The use of computer vision is used across many disciplines. In one experiment, Töreyin, et al. created an algorithm to detect fire and flames in videos and real-time [5]. Other research groups are using computer vision to detect the use of detecting falsified pharmaceuticals [20], the overall quality of food products [21], and for various applications of facial recognition [22, 23, 24]. The examples listed are only a few instances in which computer vision has been used. This shows how diverse the use of computer vision can be across disciplines. In recent years, one of the largest uses of computer vision has been in the area of roadway and urban safety. Using computer vision in combination with an object detection algorithm, individuals have been researching how to better detect pedestrians, vehicles, and objects on the roadway to lessen the occurrence of roadway accidents [8, 25]. An example of an implementation pertaining to vehicular and pedestrian safety is see-through technology. The next section will explain a broad overview of see-through technology.

Methodology

This paper expands upon the following experiments using a see-through algorithm. This section will provide information about the implementation of the experiments to better understand how the see-through algorithm presented in this paper would benefit drivers in a real-world environment.

Experiment One: Methodology

Vehicular Setup The vehicular setup (see Figure 4) involved three vehicles aligned linearly front to back at The University of Tennessee at Chattanooga's (UTC) campus testbed. The campus's testbed consisted of a four-lane street (two lanes for each direction) and three APs connected to fiber optics internet (see Figure 5). Two of the three vehicles were equipped with a web camera that was placed on the windshield to view the back of the vehicle in front and connected to a laptop acting as a client. The clients were used to capture and transmit the images taken by the web cameras to an offsite server for image processing.

Wireless Setup The wireless communication consisted of three APs on electrical poles approximately 3.3 meters from the ground along the sidewalk of the testbed. The placement of the APs (which used a frequency of 5Ghz) along the street allowed an overlapping wireless connection for the laptops within the vehicles. Each AP was connected to Chattanooga's fiber internet, which gave the APs a potential data transfer speed of up to 10-Gbps. This greatly reduced latency time when testing the image transfer and processing with the off-site server, which was also connected to fiber. A representation of this testbed can be found in Figure 5.

See-Through Algorithm The goal of experiment one was to allow the rear vehicle to be able to "see-through" the middle vehicle and increase the driver's knowledge of the overall driving environment. To achieve this goal, a thirty-two layer pre-trained CNN was used to identify the objects of interest in the images. In the case of this experiment the objects of interest were vehicles. While the imaging program was running, each of the cameras captured a continuous series of images and sent them to an offsite server via the connection between the clients and APs along the street. The server then incorporates its graphics processing unit (GPU) for the use of multithreading to analyze each of the image feeds simultaneously to check for any objects matching or related to the image data found in the CNN model. If there is an object found, the program will create a visible bounding box around the object for the driver's visual reference. If the rear vehicle is close enough to the middle vehicle for the see-through to be activated, the server will overlay the image from

FIGURE 4 Example of the vehicular setup used. Three vehicles lined back-to- back with an access point located within the range of each vehicle to allow for continuous data transfer and a web camera placed on two of the three vehicles for image capturing.

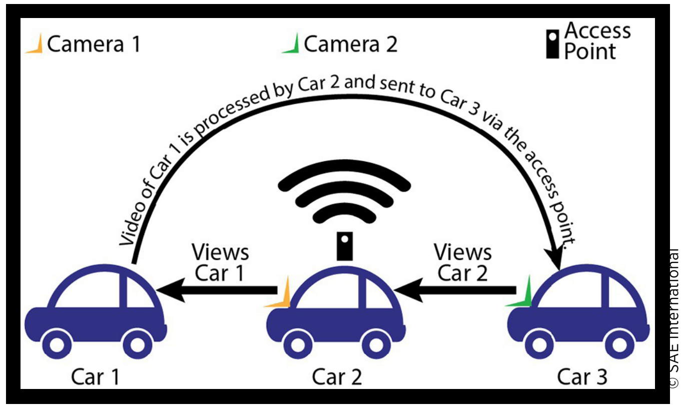
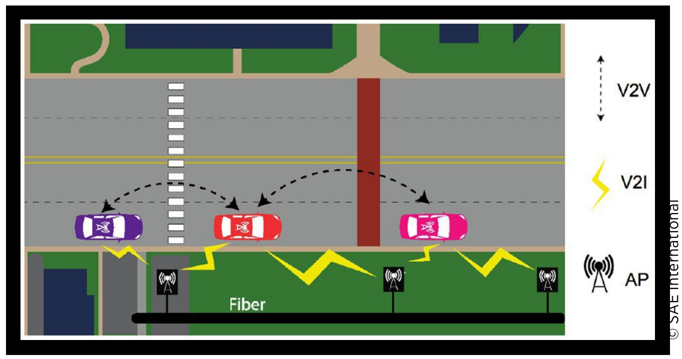


FIGURE 5 A graphical representation of the testbed on UTC's campus consisting of a two lane street in each direction, a crosswalk, and APs connected to Chattanooga's fiber optics internet. This image shows V2V and V2I communication with the assistance of the APs.



the middle vehicle onto the center of the object bounding box detected by the rear vehicle. The overlapping of the images result in a continuous image feed as long as the rear vehicle is close enough to the middle vehicle to identify it and activate the see-through process. This continuous overlapping allows the rear vehicle to "see-through" the middle car and expand the driver's field of view. Figure 6 shows a representation of the image transfer and overlaying process.

Ultimately, with the combination of the wireless communication connected to fiber and the enhancement of the see-through algorithm used, the overall latency was one second or less. Figure 7 shows images taken from a recorded video of our experiment from the view of the rear car. These images would be for the use of the driver to broaden their field of vision to better understand their full driving environment.

To minimize the distraction of the see-through visualization presented, the feature itself could be viewed as an optional assist feature using a visual or auditory alert when the driver should be notified. The visualization would not be active

FIGURE 6 A graphical representation of the algorithm's overall image transfer and processing procedure through the clients and offsite server. The images are sent from the clients to the server, processed simultaneously, and send back to the rear vehicle with the feeds from both vehicles combined.

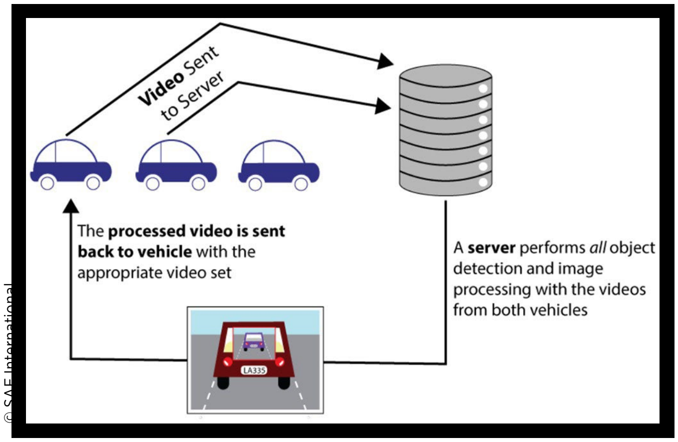
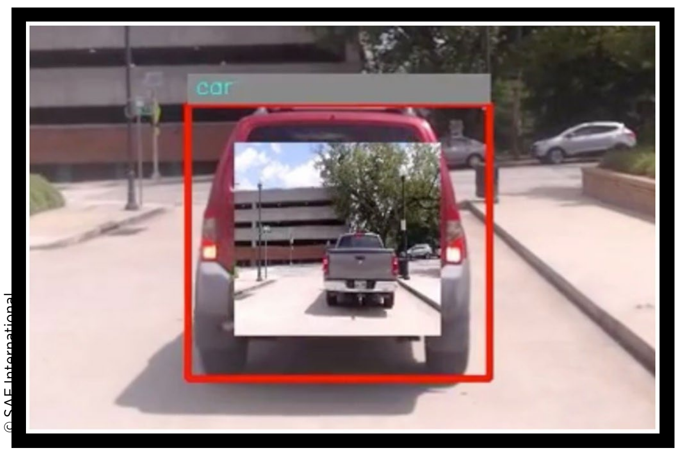


FIGURE 7 An example of the see-through algorithm activated from the perspective of the rear vehicle.



throughout the duration of driving time, but it could be activated when the driver is within a set range of itself and the vehicle in front. This range can be a manually set distance or activated once the vehicles have been wirelessly connected and ready to receive data from each other. Other than the driver needing to understand how to interpret the image shown, the see-through component would be completely passive and would need no further interaction from the user once activated.

To further explore the concept of see-through technology for the use in roadway safety, the differences in a driver's ability to see an object in their field of vision with and without the see-through algorithm presented was tested. The likelihood of continuously being located in an area with APs connected to fiber is not always plausible. To account for this, the next section describes a second experiment where APs connected to fiber and a group of APs for separate connections are unavailable.

Experiment Two: Methodology

In addition to experiment one, a second experiment to further identify the benefits of see-through was performed. The previous experiment involved the use of V2I access points to simulate the potential of this application in an ideal environment where both V2V and V2I capabilities are available. In this experiment V2V communication is the focus of the wireless communication system. In the event of no V2I access points, how would see-through technology still benefit driver awareness while using V2V communication instead of both V2V and V2I communication? This experiment takes this question into account as well the case of having no offsite server for collecting, processing, and returning the images with a multi-threaded system. The image processing for this experiment was done by the laptop that is receiving the image from the vehicle in front; in this case, the rear vehicle acts as the server and processes the images from the front vehicle. This experiment was performed to examine the potential benefits see-through can give drivers in the case of V2V communication and local computation only.

Vehicular Setup The vehicular setup for this experiment is similar to that of experiment one, but instead of using three vehicles for the experiment, only two were used. See Figure 4 for a representation of the vehicular setup.

Wireless Setup A wireless router was placed on the rear vehicle to allow a local connection by the laptops within the vehicles. The router was set to a 5Ghz frequency to allow improved communication between the vehicles and laptops. Using 5Ghz provided sufficient bandwidth to support continuous transfer of the data in the case of an object blocking the direct path between the router and the laptop from the front vehicle.

See-Through Algorithm The see-through algorithm used was the same algorithm used in experiment one, with the exception of sending the collected images to the offsite server. Instead, a laptop placed in two vehicles were running a custom-written Python script to capture video with the current time based of the local time from the operating systems. After these videos were captured, they were later processed using the same see-through algorithm as experiment one. Compared to experiment one, this process was done without multithreading and also used a less powerful GPU than experiment one. Though the GPU was less powerful, similar results in time differences between the frame in which the rear vehicle can see the obstacle in its frame verses the see-through frame were found. In the next section, we will take a look at the results from each experiment.

Results

The following results are divided into two sections based on each experiment performed. The first section of results will be pertaining to experiment one. The second section of results will be pertaining to experiment two. The experiments are divided into two separate sections to compare each case individually. In the Discussion section, all scenarios presented in this section will be discussed as a whole. In each results section, the results shown were implemented and recorded by screen recording software in real-time. The times states in the descriptions are based on the time that particular event appeared in the frame compared to the overall time of the recorded video.

Experiment One: Results

Blocked Lane In Figures 8 and 9, a scenario of a lane blocked by another vehicle is shown. In this case, the lane was blocked by a truck owned by an electrical company. In the recorded video, the event of the truck appearing within the rear vehicle frame was at 7:14 (Figure 9) whereas with see-through in effect, the driver of the rear vehicle was able to determine something was blocking its lane at 7:11 (Figure 8); this is a 3 second time difference. If the rear vehicle had been driving too close to the vehicle in front or had see-through not been activated, the driver of the rear vehicle would have had less time to react to the situation and potentially have caused an accident that would have endangered themselves and the workers that were in their line of sight. The extra 3 seconds given to the driver could have been the difference between endangering lives and the ability to make a decision to keep all parties safe.

Another observation based on this scenario is that by using see-through not only did the driver of the rear vehicle gain an early view of the electrical workers, they also gained a view of the lane to the left of the truck that would have been blocked by the vehicle in front had see-through not been available. Having this extended view before the truck was within the rear vehicle's viewpoint allowed the rear vehicle to smoothly pass the truck along with the car in front instead of having to stop to make sure no vehicles were driving in the opposite direction toward them before proceeding.

FIGURE 8 A screenshot showing the lane being blocked by an electric company's truck from the viewpoint of the rear vehicle with the see-through algorithm activated.

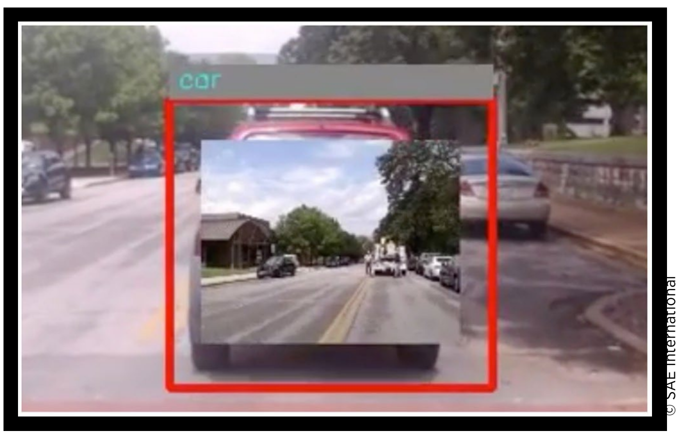


FIGURE 9 A screenshot showing the electric company's truck entering the full view of the rear vehicle's line of sight. This image also shows the driver of the rear vehicle the lane to pass the truck is clear of vehicles driving in the opposite direction and they can follow the vehicle in front to safely avoid the electrical truck as well as the workers.

Experiment Two: Results

Road Debris In Figure 10, an object was placed in the center of a parking lot lane. To avoid this object, each of the vehicles would have had to shift to the opposite side of the lane or stop, in the event of a vehicle traveling in the opposite direction in the same lane. In the recorded video, the time at which the object was in the frame of the rear vehicle without see-through was at 0:32 (Figure 11). The time at which the object was in the frame of the rear vehicle with see-through was at 0:30 (Figure 10). This gave the driver of the rear vehicle an extra two seconds to decide what action to take to avoid the object. As mentioned in a previous example where an electrical company's truck was blocking the lane, the see-through capability also gave the driver of the rear vehicle an opportunity to see whether another vehicle was driving in the opposite direction towards them while the vehicle in front is actively avoiding the object by switching lanes and act accordingly.

Pedestrian Crossing In many cases of a pedestrian crossing the street, the vehicle furthest away will be able to see the pedestrian before the vehicle in front of them, but what if they are distracted by something? What if they do not see the

FIGURE 10 A screenshot of the road debris shown to the rear vehicle via the see-through algorithm before entering the rear vehicle's field of view at second 0:30.

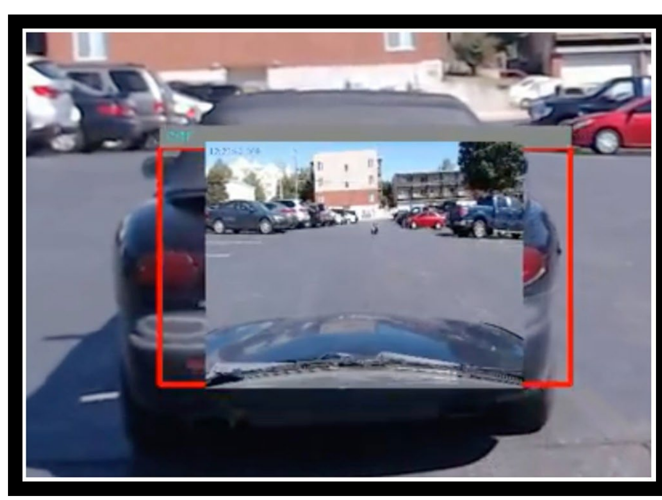
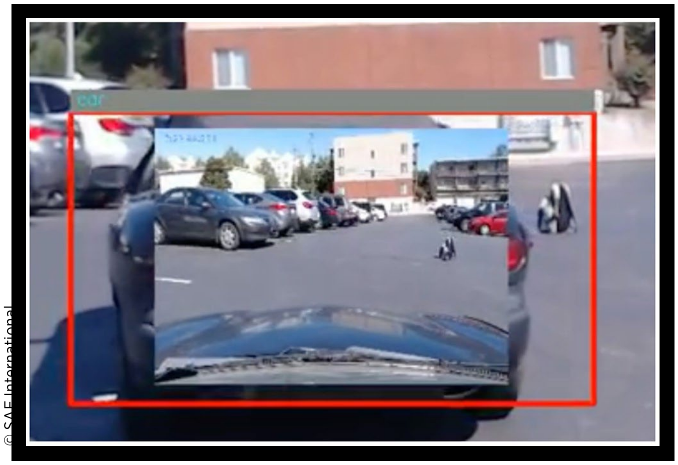


FIGURE 11 A screenshot of the road debris shown after the road debris has entered the rear vehicle's field of view at second 0:32.



pedestrian beginning to cross, decide the car in front of them is stopping for no reason, and go around them? That driver has now put a life in danger because of their lack of awareness to their driving environment. By using see-through, the driver in the rear vehicle is able to see a pedestrian crossing the street for the duration of the time the pedestrian is present both in the first vehicle and the rear vehicle's line of sight. This gives them the opportunity to see that there is someone crossing the road regardless of whether they were distracted by a sign, person, or even a text. In the case of the experiment shown in Figures 12 and 13, a three second difference was recorded from the time the pedestrian entered the field of vision for the see-through image at 1:01 (Figure 12) of the recorded video and the field of view of the rear vehicle at 1:04 (Figure 13).

Discussion

In the results section, each of the scenarios were observed using a real-time implementation of the see-through algorithm presented in this paper and a screen recorder to film each experiment. In each scenario, a time difference between the point in which the rear vehicle could see the obstacle in its primary frame without see-through versus the time it could see the obstacle in its frame with see-through was stated. Each of the times were based on the time the scenario appeared on the recorded video from the experiment. Table 1 shows each of the times individually from each scenario presented and the difference between the two times to show the consistency see- through has with giving the driver of the rear vehicle an early awareness of the obstacle. This excess time gives the driver more opportunity to react to the situation and be able to think more clearly about what actions need to be taken to avoid a collision or accident. Table 2 shows the absolute worst, best, and average time difference taken overall from the experiments performed. The time shown is the time difference in seconds that the driver of the rear vehicle was able to see an object in the road and react using see-through compared to not using see-though. Table 2 can be interpreted similarly to

FIGURE 12 A pedestrian crossing the street being viewed by the rear vehicle via the see-through algorithm

FIGURE 13 A pedestrian exiting the view of the front vehicle and the see- through algorithm's field of view from the front vehicle and into the rear vehicle's field of view.

Table 1 with the exception that Table 2 encompassing the time differences from all experiments performed.

Being that these experiments are preliminary experiments for the overall see-through concept being developed, the following are important factors to take into consideration relating to the results presented and discussed in this paper:

Vehicle Speed: The vehicle speed varied depending on the experimental environment. In Experiment One, the speed varied from approximately 15 mph to 25 mph due to the combination of the V2V and V2I communication used. Higher speeds were not tested due to the testbed being on a university campus. In the event of hardware and driving environment becoming available at an off-campus site where speeds can be increased, further research into developing the algorithm for higher speeds can be explored. The vehicle speed for Experiment Two varied from approximately 5 mph to 15 mph due to this experiment using solely V2V communication. In order to obtain a continuous video to extract results, vehicle speed was lowered.

TABLE 1 Times displayed in relation to the times from the recorded experiment videos mentioned in the results section. The times shown are: the time when the obstacle appeared in the rear vehicle's frame without see-through, the time when the obstacle appeared in the rear vehicle's frame with see-through, and the time difference between the two.

Scenario (Experiment #)	Without See-Through	With See-Through	Time Difference (in seconds)
Lane Block from Truck (Exp. 1)	7:14	7:11	3.0 Seconds
Road Debris (Exp. 2)	0:32	0:30	2.0 Seconds
Pedestrian (Exp. 2)	1:04	1:01	3.0 Seconds

TABLE 2 Best, worst, and average times (in seconds) an object can be seen earlier by a driver using see-through based on multiple instances of each experiment compared to without see-through.

Category	Time (in seconds)
Best Improvement in Reaction Time	1.4 Seconds
Worst Improvement in Reaction Time	1.9 Seconds
Average Improvement in Reaction Time	2.3 Seconds

Image Resolution: The image resolution was scaled to 448x448 pixels to effectively run through the CNN used. This allowed the CNN to analyze the images at the same resolution each time to minimize any type of image distortion and decrease the probability of misinterpreting a feature within the image.

Frame Rate: The web camera used in this experiment captured images at 30 fps. Though this was the frame rate, the algorithm only processed one frame every ten taken to reduce latency while analyzing frequently enough to gather important data for a real-time interpretation.

Conclusions

In this paper we presented two experiments using a single camera on a set of vehicles, a set of access points for one experiment, and an algorithm built upon a convolutional neural network to identify vehicles and pedestrians to expand upon the concept of see-through technology. By using a CNN, the identification of an object in an image feed allowed the ability to create a dynamic output of overlapping images from one vehicle to another to create the illusion of being able to "see-through" the car in front with the driver's own eyes. Not only does this ability increase a driver's view of the roadway environment, it also allows the driver to have a higher sense of awareness.

As stated in the beginning of this paper, distracted drivers made up 10% of the roadway crashes in 2015. This Introduction also discussed an example of how 2 seconds can make the difference between life and death: "According to their findings of the 85th percentile reaction time values, the range of driver reaction times were between 1.26 and 3.6 seconds" [6]. Depending on the way that see-through is implemented, it can be used to actively *alert* with a sound as well as by - at the moment of the alert - making see-through available. With a tool like this to redirect your attention back to driving, this reaction time can be improved by those 2 seconds.

From the results explained in this paper, see-through technology allows a driver a look into what is to come on the roadway and gives them more time to think and take action. Though see-through is not the complete solution to prevent distracted drivers from avoiding accidents, the ability to give the driver at least two to three extra seconds to be aware of an obstacle in their path could be all the time they need to evaluate their surroundings and take the correct action to prevent endangering their lives or the lives of others.

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Contact Information

Rebekah Thompson, M.S. Computer Science Candidate
University of Tennessee - Chattanooga
dys548@mocs.utc.edu

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Definitions/Abbreviations

V2X - Vehicle-to-Everything

V2I - Vehicle-to-Infrastructure

V2V - Vehicle-to-Vehicle

AP - Access Point

UTC - University of Tennessee at Chattanooga

CNN - Convolutional Neural Network

NHTSA - National Highway Traffic Safety Administration

RGB - Red, Green, and Blue color/light channels

2D - Two Dimensional

3D - Three Dimensional

HOG - Histogram of Oriented Gradients

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