Detecting Fatigue Driving Through PERCLOS: A Review

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Abstract

In this paper, we present a literature survey about drowsy driving detection using PERCLOS metric that determines the percentage of eye closure. This metric determines that an eye is closed if the percentage of eye closure is 80% or above. When this percentage is observed for multiple frames of a video camera feed, the driver is determined to be in an unsafe fatigue status. In our research, we found that the PERCLOS metric had a 0.79 to 0.87 correlation coefficient value which exceeds the 0.7 R value needed to be considered a strong correlation coefficient. A higher value than 0.7 indicates a more linear relationship which means that the metric is dependable [1].

Keywords: PERCLOS, Real-time Systems, Autonomous Driving.

1. INTRODUCTION

In this modern age, many people go to work, school, and other places using their transportation. According to a 2018 census from Statista Research Department, there is a recorded 276 million cars in the United States. While public transportation use may be increasing, many Americans certainly use cars as their main form of transportation. Since there are many cars on the road, the chances of being involved in a car accident are high. Although many motor accidents occur year-round, there is one cause that reoccurs, drowsy driving, and the rate of these accidents is steadily increasing. According to the National Highway Traffic Safety Administration (NHTSA), there were an estimated 91,000 accidents, 50,000 people injured, and 800 deaths due to drowsy driving in 2017 alone. However, it is agreed by sleep science, traffic safety, and other health communities that the number of accidents is an underestimate of the people injured or killed by drowsy driving. Some say that there could be potentially 6000 fatal car crashes. From this information, it is clear there is a need for ways to prevent drowsy driving. These dangers have stemmed from research on creating the most effective way to alert the driver when they are detected to be drowsy. After looking at numerous scientific papers on the topic of drowsy driving, the topic for this survey paper was narrowed down to drowsy driving detection through the use of eye detection and blink counting, particularly the ones that employ the use of PERCLOS, which is an eye detection method that involves detecting when the eye is at least a certain percentage closed, most cases being 80% closed from its normal state.

The reason behind this survey paper is to answer the question of whether drowsy driving detection with eye and blink detection was viable in widespread use. To gauge the effectiveness of the system, we were interested in both the success rate of the system, and whether it can be implemented with as little hardware as possible. These two factors were highly considered when we were searching for research papers. After we parsed through the papers, we were able to find the similarities and differences between each implementation of a drowsy detection system. The main thing we wanted to find out was if it was possible to create a system with minimal hardware that could have a success rate of 80% or higher. Throughout this paper, we will discuss the similarities, differences and the overall usefulness of each implementation.

2. PROBLEM STATEMENT

Is it possible to create a minimal hardware implementation with a success rate of 80% or over? This was the question statement we wanted to answer when writing this paper. Just from initial screening of the research papers we looked through, we came up with a hypothesis that it is possible to create a system that has minimal hardware and functions with an 80% or over succession rate. We came up with this hypothesis because we were able to find evidence that other implementations have successfully created the system that we seek. To prove that a system exists, we will go over the evidence we have found.

3. CHARACTERIZATON OF CLASSES

We brought up that the two key factors to determine if the system is valid or not were the success rate of the system, and the cost of the implementation.

3.1 Class 1

One of the more popular papers that fit these criteria was titled “Real-time nonintrusive monitoring and prediction of driver fatigue” by researchers Q. Ji, Z. Zhu, and P. Lan [2]. Though this is not the most recent paper out there, it has been cited in 358 other papers as of the writing of this survey paper. Their system focused on creating a way to predict driver fatigue in a way that was non-intrusive and involved using two cameras, outfitted with infrared LEDs to brighten the driver’s face and make eye detection/eye tracking easier. Through a validation process by the research team, they were able to determine the success rate of approximately 95.75% with 0.05% of the failure coming from false-positives and 4.2% coming from missed readings.

3.2 Class 2

The next research paper is an even older one that also has several citations titled “A drowsy driver detection system for heavy vehicles” by R. Grace, V. Byrne, D. Bierman, J. Legrand, D. Gricourt, R. Davis, J. Staszewski, and B. Carnahan [3]. This paper was written way back in November of 1998 and has been cited in 49 research papers and 24 patents. As this was an older paper, the technology available to them was limited. The camera that this research team had used had a maximum frame rate of 6 frames per second and was said to correlate “very highly” with manually coded data and had a high repeatability given the same datasets.

3.3 Class 3

The next research paper that we had found to fit our criteria was a paper titled “A method of driving fatigue detection based on eye location” written by L. Li, M. Xie, and H. Dong [4]. This paper introduced a method to locate the eyes based on Active Appearance Model (AAM). This system consists of narrowing on the eyes through different filters and AAM. It first uses an Adaboost algorithm module to get a rough location of the face and eyes. It them uses the AAM model to match the image to the training samples and accurately locate certain features of the eyes. Once the features of the eyes are known, the PERCLOS score can be calculated. This paper goes on to explain some of the limitations that may occur with a system that involves only a camera since things such as lighting, movement of the driver’s head, or eyewear can throw of the detection. The researchers of this paper did not include the success rate of their system, but the hardware used, being only the camera to record the driver, did not seem expensive.

3.4 Class 4

M. Poursadeghiyan [5] had a research paper that fit our criteria. According to their research paper, “Using Image Processing in the Proposed Drowsiness Detection System”, they were able to create a system that had a success rate of 93% which is high above the requirement that we set as a baseline. The implementation used a camera to take a video of the subject. Each frame in the video would be checked for the coordination of facial details. Using the Viola-Jones algorithm, each frame of the video would be checked for specific facial landmarks of the eyes of the driver. To find out if the driver’s eyes were closed or not, the frame would be converted to grayscale and checked to see if eyes are closed or not. We then checked to see how they implemented their system. According to Poursadeghiyan [5], the system they used required extensive equipment including a virtual driver simulator, computer, and camera. Indeed, the system worked with high success, but it couldn’t meet our mark of using minimal hardware. Aside from the simulator used to conduct the research, the computer and camera system they used requires more space than other systems. Because of this, we continued to look for other implementations that could satisfy our two requirements.

3.5 Class 5

The next paper we looked at was by C. Xu [6] and it was cited by 5 other papers along with a patent. According to “Efficient eye detection in real-time for drowsy driving monitoring system”, Xu [6] was able to create a system by using a Local Binary Pattern histogram to create a histogram of the eye region and then passed through an Adaboost cascade classifier. This classifier would be trained by the numerous histograms and it would be able to determine if the eye was closed or not according to a PERCLOS score. After looking at this paper, we were able to identify that the success rate of this implementation was averaging 98% success. This system’s success rate was way above the requirement we set so we wanted to see what kind of equipment was being used to create this system. We noticed that for this setup, it was not explicitly stated that it could have been created with minimal hardware.

3.6 Class 6

According to “Sober-Drive: A smartphone-assisted drowsy driving detection system”, L. Xu [7] used a system that leveraged the PERCLOS metric to train a neural network that could identify if the driver was drowsy or not. The more important factor was that for the first time looking through our papers, we were able to find a system that could be implemented with minimal hardware. Xu’s [7] implementation could run on an android phone without any other equipment. Also, according to this research paper, the success rate of their implementation was averaging a 90% success rate. This implementation system satisfied both factors we set at the beginning of our paper. The success rate was above 80% and it could function with minimal hardware, which for this system was using an android phone. Xu’s team's implementation used a neural network to determine the drowsiness of the driver.

3.7 Class 7

According to “Efficient Measurement of Eye Blinking under Various Illumination Conditions for Drowsiness Detection Systems”, I. Park [8] was able to implement a system using a standard 2D camera plus two IR illuminators and a computing power of some sort. As stated by the paper, Park’s team was able to have an average success rate of 94% without illumination compensation and an average success rate of 98% with illumination compensation. Both success rates far exceeded the baseline of an 80% success rate. The second factor was somewhat satisfied as the system itself doesn’t require as much hardware as other implementations, but it is not the smallest it could be. The software that was created was like the first two systems that are previously discussed above.

3.8 Class 8

The last system we looked at was the best system that we found since it exceeded our expectations for both the success rate and the use of minimum hardware. Professor Y. Cheung and his fellow researchers created a system that would detect the eye region of the driver's face and find the distance between the eye corner and the iris to detect whether the driver was falling asleep or not. According to "US Patent: US9,563,805" [9], Cheung's system was able to have an average success rate of 93%. Cheung's system was also implemented in a cell phone, so it passed the criteria of using minimum hardware. This system was the most effective system out of all the ones that we found in our sources. The combination of having a high success rate plus being able to run it on low-end cell phone hardware stood out as being overall the most effective implementation for detecting drowsy driving.

Techniques for Drowsy Driving Detection	Classes
Using multiple cameras includes use of multiple 2d camera, IR camera, depth sensing camera.	1, 7
Using single camera	2, 3, 4, 5, 6, 8
Using neural network to compute different scenario	3, 4, 5, 6
Detection through distance measurement	8
Mobile hardware implementation	6, 8
Desktop hardware implementation	1, 2, 3, 4, 5, 7

4. COMPARATIVE EVALUATION

In the previous section, we were able to categorize each class with certain categories. It was common to see overlap between each of the classes but at the same time, we were able to identify clear differences. In this section, we want to discuss how each system compares to each other and possible changes to make a hybrid system. We will back up our recommendation based on the chart provided above. Looking at the first category, it was surprising to see that not many implementations used multiple cameras to detect drowsy driving. However, there was two implementations that used multiple cameras. However, the success rate was not much higher than other implementations. The next technique was using only one camera for the overall system. This was much more common, and every single implementation had a success rate of over 80%, so having one camera wasn't a disadvantage. It is an advantage because those systems would require less hardware to make their system work. Our recommendation for between these two techniques is to use a system with one camera since the success rate is around the same as other multiple camera implementations and it would require less equipment. The next two techniques dealt with how each system identified a drowsy driver. The first technique was to use a machine learning network that was trained with images to differentiate between awake and drowsy drivers. In practice, the implementations that used neural networks/machine learning tended to have higher success rates than the ones that used distance measurements from camera data. The second technique was to directly use the camera data to find if the driver was drowsy or not. For example, packages such as OpenCV, have methods that can give researchers data to calculate the distance that is used to identify if the driver is drowsy or not. This method will exceed the minimum 80% success rate and require less memory because it doesn't need image data to compare too. For our recommendation, we would choose to use the machine learning with one exception. Researchers should process and store the data necessary for the neural network on the cloud so that local memory allocated to the device is to a minimum. This is important for the next technique. The last set of techniques deals with how the hardware is packaged. The first technique is to use a mobile implementation, more specifically, a mobile phone. The benefits to using a mobile phone as a computing device is that the access to smartphones in this decade has been more readily available than it has in the past. With more mobile phones, providing an application can be better for more widespread use compared to proprietary hardware. The second technique is to use desktop hardware which could provide more computing power at the cost of portability. Between these two techniques, we recommend using the mobile implementation as it provides the most ideal power to portability ratio. To recap, we would recommend creating a mobile application that uses a single camera and processes information using a neural network specifically on the cloud.

5. CRITICAL DISCUSSION

In the last section, we discussed the different implementations of drowsy driving detection systems and how each system was able to meet our two conditions of having a success rate of over 80% and using minimal hardware. We also discussed how each implementation had similarities and differences. At the end, each system met our conditions, but we wondered how we could potentially make the systems work better. There have been many technical advancements in the last couple of years that could potentially make these systems better to use. The first tool we would recommend new researchers in the area would be to take advantage of cloud computing. For example, the popularity of services such as Amazon Web Services (AWS), Microsoft's Azure, or Oracle's cloud service are just a glimpse of what researchers could use to create more effective machine learning processes without it bogging down the system on the device itself. The main purpose of these services would be that instead of created a locally based system and potentially hogging memory space, the algorithms that are necessary to detecting drowsy driving would be computed on the cloud and sent to the device. This is key for mobile implementations of drowsy driving detection. We need to take into consideration that the less space that is necessary for the system can create better access for people who don't have as much storage on their mobile device or for creating hardware for less money. The drawback to this system would be the need for a constant data connection so it wouldn't be viable in countries where cellular reception is not developed. The potential for creating a system that is integrated with cloud computing can expand the use of the drowsy driving detection to other types of detection system which could be more helpful as autonomous vehicles become more popular. Another recommendation we would give to researchers would be to take advantage of the latest cell phone hardware. As we were reading through our multiple sources, it became clear to us that the papers we were reading were using dated hardware. With current technological improvements, it should be mandatory to use the latest hardware. For example, a budget phone with enough power would of cost around 200 to 250 US dollars. However, with the power of competition, we can find hardware that has more processing power for even under 100 US dollars. We can also expect that this advancement in hardware will continue to progress as accordance to Moore's law. These are a couple recommendations we can give that could help further improve the current drowsy driving implementations.

6. PROS AND CONS

After looking through all our sources, we were able to identify the systems and how each one was implemented. From our analysis, we were able to identify that many systems used the PERCLOS metric to determine if the driver was drowsy or not. However, each system differed on how it would use the PERCLOS metric. Some implementations would feed the eye region data into a classifier to train its neural network so that it could predict if the driver was drowsy or not. Others would measure different landmarks on the eyes to find the distance between these landmarks in a measurement called EYA and would base their judgment system on that information. In this section, we want to go over some of the pros and cons of each of these different systems because even if some systems got close to 100% success rate, none could perfectly identify if the driver was drowsy or not. From a general point of view, each of the systems that we discussed all had a success rate of over 80%. The success rate is very important because it does not matter how small the hardware is if the system cannot accurately detect if the driver is drowsy or not. Another benefit to all these systems is that most of the hardware can fit easily into a vehicle. One big drawback we identified is that some of these systems require fast processing to acquire data and analyze in real-time, which means implementations of a phone's processing power is difficult. The systems that have these drawbacks are the systems that use machine learning or neural networks, which trains a model to see if a driver would be falling asleep on the wheel or not. These systems are meant to run for an extended duration where they are constantly working profusely to detect and track eye movements. This amount of processing can be very demanding on a system and requires a high-end computer. However, in research that utilized android application and the PERCLOS method, drowsy driving detection was much better than the machine learning and neural network systems. Unlike the other systems that matched faces to a trained model, this one detects the face and monitors it by drawing boxes and lines to detect the key facial landmarks, the eyes. An advantage that this implementation has is that the system was able to run on much lower-end hardware and it utilized significantly less memory, which means it can be implemented into an Android phone that has a working camera.

6. PREDICTED/EMERGING TRENDS

A trend that reoccurs in each research is the development of a system that is non-intrusive and has high efficiency in terms of processing and algorithms. Most research projects on the topic of drowsy driving detection have successfully identified working procedures, methods, and implementations; In fact, the only problem that is left to solve is the size of the system and how to implement it into a device that is non-intrusive. As a matter of fact, a research study has been working to develop an algorithm that fits an embedded system by reducing the model size of a neural network. By reducing the maximum memory size, the system takes less allocation of memory when used and allows the system to be implemented into smaller devices, such as Android smartphones. Another trend that is emerging is the accuracy of these systems to detect drowsy drivers. Most of the research uses some form of a facial detection system, such as tracking the eyes for behavioral studies, head movement, and yawning, while other systems utilize machine learning algorithms to train a model through facial expressions in a database. These methods have a success rating above 80%. Because other research methods are intrusive, such as the implementation of EEG (electroencephalogram) and ECG (electrocardiogram), newer research is leaning on the use of facial detection through computing and algorithms since they are more accurate.

7. CONCLUSION

After analyzing multiple implementations, it became clear that the PERCLOS metric is highly effective. Methods covered in the papers used different approaches to detect fatigue driving but they all measured the success rate of their methods against the PERCLOS metric. The effectiveness of PERCLOS presents a sufficient evidence that it is a reliable metric to be used by researchers.

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