Final Project : Visual Search Time in Identifying Cyclists

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February 13, 2016

1 INTRODUCTION

An estimated 48,000 cyclists were injured in motor vehicle traffic accidents in 2013, over half of which occurred in low light conditions [1]. Drivers often fail to observe cyclists, making cyclists particularly vulnerable [4]. Visual Search studies provide insight into why this occurs. Visibility is certainly an issue: bike lights are often quite dim in comparison to car lights, and the intensity of the signal predictably influences performance [Engel, 1977]. Attention also dramatically alters perception. Since bikers represent rare events, drivers are not attentive to their presence. Additionally, visual search is influenced dramatically by the azimuth [2]. A bike in a bike lane falls somewhere between $30° - 90°$ lateral of the usual center of vision of a driver. Visual acuity drops dramatically as eccentricity increases, making cyclists potentially invisible to drivers [3].

Here we seek to determine how color affects biker recognition in a pseudo-realistic context. Because of the variety of factors involved, we developed an experimental procedure to test visual search for bikers against a backdrop of natural scenes filled with common distractors: cars, billboards, street lamps, and stop lights.

2 METHODS

Using `Python` in hand with its `OpenCV` bindings, we created a program the generates a sequence of images which resemble what a motorist would likely see while driving through rural, highway, and urban environments. After buffering the series of images, the program presented the images to a subject. In exactly half of the images a subject encountered, a cyclist was present with a different colored tail light. Furthermore, the subject was tasked with finding a cyclist if one was present, and then to respond in the affirmative if that was the case. The program records the subjects response as well as the time it took them to do so.

The images with cyclists in them are synthetic and are constructed in a two part process as follows. An example can be seen in Figure 2.

1. We took two photographs of cyclists found online and using `Adobe Photoshop and Illustrator` we manually cropped out everything except the cyclist itself, and then decreased the $\alpha-$ value making the cyclist look slightly transparent. This was done to ensure better blending in the final result. We chose two photographs where one cyclist was wearing very bright clothing and one where a cyclist was wearing darker clothing. Since we were primarily concerned with the affect of the tail light color, we wanted to make sure the data reflects any effects of the clothing color on response time as well. For each of the two cyclists images, we created 8 copies and drew a fully visible (max $\alpha-$ value) "blob" of a different color in the approximate location of where a tail light for a cyclist would likely be situated - one copy is left unmodified as a control. Therefore, in total there were 16 unique cyclist images.

2. The program reads in each of the 16 cyclist images, and places it within an image still from dash-cam footage captured at night. The location at which the cyclist is placed is chosen at random, but constrained to be within the inner 75% of the background image. The stills are hand selected from the footage and are chosen in an attempt to capture a myriad of lighting conditions, clutter, and perspective.

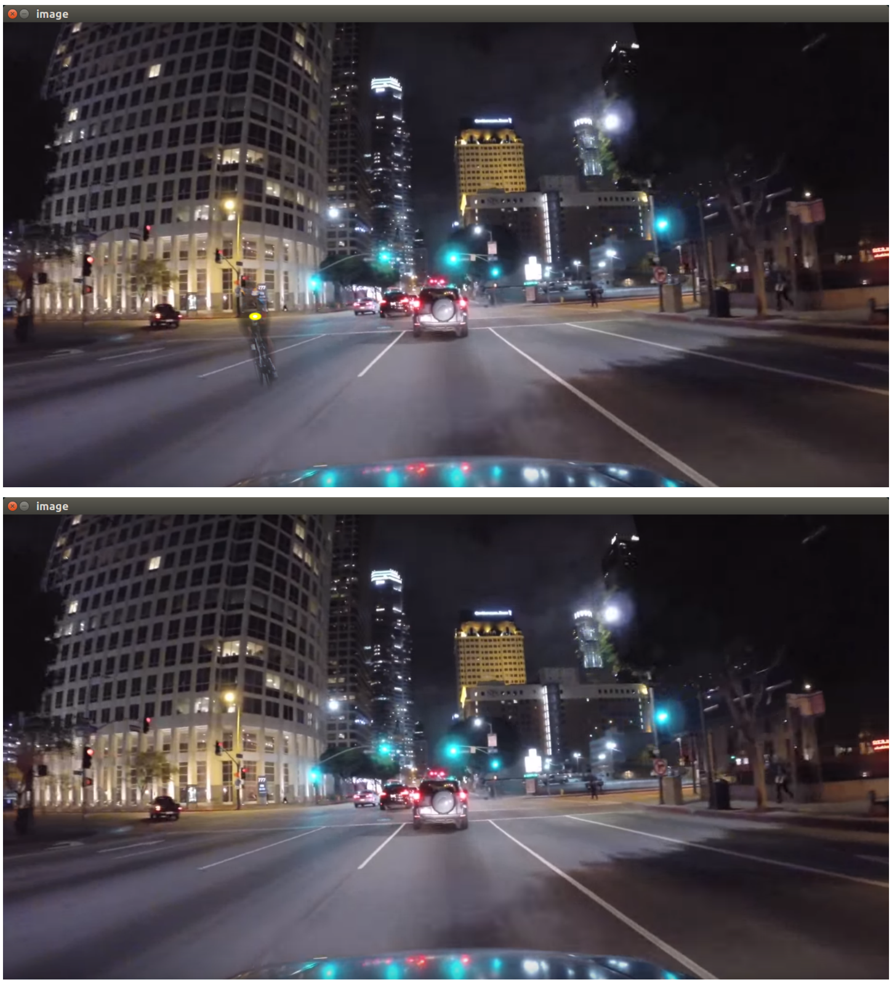

Figure 2.1: A dash-cam still with and without the embedded cyclist.

3 Results and Discussion

We observed a small effect of color on response time. (TODO Fig. 3) All light conditions were lower than the non-light conditions, with Green, Red, and Yellow lights having the lowest mean correct response times (respectively, $0.649 \pm .017$, 0.666 ± 0.020, 0.656 ± 0.018, ms, $\pm$ SEM). With green having the lowest mean time. Green and Red also had the fewest misses (TODO fig 2) with 1 each, compared to an average of 3.0 for all other colors, and 7 for no light ($n = 44$).

4 Discussion

Subjects performed best with green and red lights. While these differences may appear too small to be meaningful, at 35 mph, a car travels 51 feet per second. A difference of .1s translates to over 5 ft traveled, which could be extremely significant for whatever is in those 5 ft. Further analysis of the data shows that there was also a meaningful difference in the spread of reaction times. While the means were quite similar, different colors had a higher proportion of slow-responding outliers. The misses (marked in X's in TODO Fig. 2) also represent dramatic differences in visibility, as some lights tended to disappear into the background of similarly colored distractors. There are a range of factors that may influence why different colors performed differently. We must acknowledge the possibility that our backgrounds (which were varied, but by no means randomly created or chosen) might favor certain colors in a way that is not representative of driving experience. Additionally, this is by no means a perfectly controlled situation, and a whole range of confounding factors could be influencing the results. One question we had initially was whether red was a proper choice for bike tail lights. By convention, bike tail lights match cars' red lights. It seemed possible then that the low signal to noise ration could make red more difficult to spot. However, this was not the case. It seems likely that in driving environments, we are particularly attentive to lights of certain colors (green and red lights have particular meaning, and red lights are the steady signal for the objects we tend to look for). This could certainly compensate for the effects of noise. Similarly, pink, white, blue, and cyan lights rarely have relevance when driving. Obviously, this is speculation, but it is reassuring to know that our tail light conventions aren't necessarily making us less safe. One of the initial motivations for this study was to understand what factors make bikers more visible. In researching prior work, we came across a study showing that reflective clothing, especially on the legs, improves visibility far more than bikers predict [4]. In preparing the experiment, we found that the cyclist's body was a far more salient stimulus (popping out so strongly that it requiring significant modification to make the comparatively small light source a factor.) Thus cyclists interested in visibility should perhaps worry less about tail light color, and instead add reflective clothing to make their body more visible.

References

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