Vision Based Traffic Light Triggering for Motorbikes

Tommy Chheng
Department of Computer Science and Engineering
University of California, San Diego
tcchheng@ucsd.edu

Abstract

Current traffic light triggering is based on inductive loop sensors. Unfortunately, motorbikes (scooters, motorcycles, etc) have a difficult time triggering these sensors. In this paper, we propose an image processing algorithm to detect motorbikes at a traffic stop using a fixed camera. The algorithm tracks the trajectory of the objects in the footage by motion segmentation and connected component labeling. Classification can be created to categorize these objects as incoming traffic based on the object's trajectory. To handle different lighting conditions in the motion segmentation, we take a dual approach by selecting RGB or Opponent colorspace. RANSAC is utilized to help trajectory creation. Experimental tests using real video footage exhibit robust results under varying conditions.

1. Introduction

This paper offers an algorithm to detect an incoming motorbike for traffic light triggering. The motivation is to solve a particularly dangerous situation for motorbikers. Motorbikes do not trigger the inductive loop sensors for the traffic lights and riders are left with little alternatives besides running the red light. This problem is most apparent at night time when less full size automobiles are present.

Using a passive system such as a fixed camera connected to a computer system for processing has high potential as a solution. Cameras are non-obtrusive and can be robust in terms of maintenance and cost. To install or fix current inductive loop sensors, the road itself has to be closed. The road has to be torn to access to the sensors. On the other hand, a camera triggering system would be off the road and allow easy installation and servicing. A high mount placement would give the best results due to less occlusion by cross traffic. In some cases, many traffic intersections already have similar infrastructures in place with red light camera systems.

There has been much work in the field of vehicle detection for traffic applications but very little work has been tested on motorbikes. The objective of this project is to

Figure 1. Most motorcyclists are left stranded because current traffic light triggering sensors cannot detect their motorbikes.

demonstrate an algorithm to detect and track a motorbike for traffic light triggering. The methods used in this project are variations of conventional image processing techniques. We use image subtraction to obtain the motion segmentation of the footage. The background frame used is a sliding temporal average window. Accordingly, RGB colorspace is used for nighttime and the blue-yellow channel in the opponent colorspace is used for highly illuminated conditions such as daytime. A simple selection algorithm can select the colorspace based on a pixel intensity average. Binary thresholding and connected component labeling are applied to label the objects. RANSAC is used for partial line fittings to create robust trajectory lines. At this stage, we can classify objects as incoming traffic based on its trajectory. Ideally the techniques used in principle should work on automobiles. Some testing has been done on footage with automobiles but the main focus and parameter tuning has been set for motorbikes.

2. Previous Work

Motion segmentation is a common image processing technique. *Y. Liu et al.* [1] presents a similar algorithm in segmenting automobiles from the background. This algorithm utilizes HSV colorspace mapping. We found using the blue yellow channel in the opponent colorspace proved more reliable than HSV for daytime illumination conditions. *V. Bhuvaneshwar et al.* [2] also utilizes a similar background subtraction for pedestrian detection.

The other field of tracking involves tracking by feature points. The KLT tracker [4] is an example of this method.

Our main goal was to utilize tracking solely for incoming traffic detection therefore a simple tracking based on motion segmentation and connected component labeling would be suitable.

3. Approach

3.1. Motion Segmentation

The motion segmentation algorithm applied is a variant of the common image subtraction technique. Image subtraction is often used to recover motion from a video footage. The background image is defined as all the static objects in the footage while the result of the image subtraction will give all the moving objects in the foreground. Defining the background image is the variation.

Many projects define the background image to be the previous frame or a set empty frame. We define the background image to be a sliding temporal average window of the previous n frames. In our case, we set n to 15 frames. A sliding temporal average window proved to be most effective definition of the background image. Using just the previous frame gave low subtraction values when the motorbike was traveling at a slow rate. Additionally, using a set empty frame is possible but very susceptible to difficulties with camera vibrations or changing conditions.

We used a dual algorithm for the image subtraction by selecting the colorspace. In late evening and nighttime, we used RGB subtraction. The headlights of motorbikes are defined cleanly against a dark background. In daytime, the lighting conditions are illuminated and motorbikes are difficult to distinguish from the background using RGB. We used only the blue/yellow channel in the opponent colorspace for daytime image subtraction. We discarded the luminance and red/green channel.

RGB colorspace for image subtraction on daytime footage proved very ineffective at segmenting the motion of an incoming motorbike. Our first alternative was the

(a)

(b)

(c)

Figure 2. (a) Original video frame. (b) Image subtraction using RGB. (c) Image subtraction using the blue/yellow channel of Opponent colorspace.

L*A*B* colorspace. The highly non-linear definitions of L*A*B* proved to be ineffective with low resolution imaging. We had also tested the HSV colorspace. We applied image subtraction on each component separately. The result was a noisy image. If we solely use the value (or intensity) component, the motorbike was present but it was also sensitive to noise creation.

We used opponent colors in hopes that the nonlinear definitions (compared to L*A*B*) would give better results on low resolution video. Using just the blue/yellow channel proved to be most effective and we elected to use it for high illumination scenes.

The selection algorithm computes the average RGB pixel value in the current frame and if below a certain threshold (we used 100), the image would be considered low luminance (night time) and we select RGB colorspace. Otherwise, we select the opponent colorspace for processing high luminance footage.

3.2. Tracking

3.2.1 Connected Component Labeling

A binary threshold is applied to reduce noise and allow a connected component labeling. 8-connectivity is used as the parameter for the labeling algorithm. We compute the centroid, area and bounding box of each labeled object in the frame.

3.2.2 Motion Tracking

In the first frame of the captured footage, we store all the labeled objects into a global data structure. In all succeeding frames, we subtract each object's centroid from every object in the global data structure. We consider the minimum distance object as a possible match for the current object. If the object is below a threshold distance difference and area difference, we assume it is the same object. We add the current object's centroid location to the position list of the matched object in the global data structure. If there were no objects in the global data structure that were within the threshold distance and area difference, we add the current object to the global data structure.

3.2.3 RANSAC Partial Line Fitting

To aid in trajectory creation, we utilize RANSAC [3] to create line models from each object's position list.
RANSAC is used in the following manner:

1. Select two points from an object's position list.
2. Create a line model from these two points. (i.e. C1X + C2Y + C3 = 0)
3. Compute y-values from the x-position list using the new line model.
4. Compute the distance of the estimated y-values with the real y values from the position list.
5. If the distance is within an error threshold, add it to the list of inliers.
6. If the list of inliers is greater than a set count threshold, consider it as a possible trajectory path for the given object.
7. Repeat this procedure for every two points in the object list.

To limit the number of similar lines produced, we limited the computation to three decimal points. In Fig. 3, a motorcycle merged with an opposing car's path and the motion tracking mis-tracked the objects. RANSAC allows robust trajectory estimation by a partial line fitting even in the presence of wrongly tracked objects. With the RANSAC algorithm, we can still estimate the motorcycle's path for classification as incoming traffic.

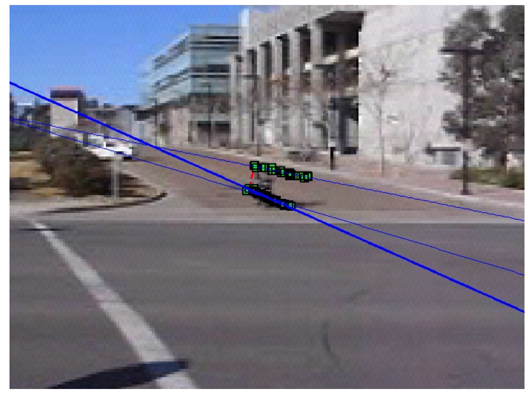

Figure 3. RANSAC is utilized to create robust trajectory estimations from data points.

4. Experimental Results

We setup our fixed camera next to an intersection to capture video footage. The resolution was set at 320x240, 15 frames/sec. We selected a lower resolution to better simulate the application with real-world low cost cameras. The camera was approximately five feet off the ground and facing incoming traffic. Due to restrictions of this particular location, we were unable to position the camera higher. A higher position mount would help reduce occlusion.

Tests were conducted in day, evening and night conditions with a motorbike alone and mixed with traffic. The footage was spliced into short clips for ease of testing.

As seen in Fig. 4a and 5, the proposed algorithm is able to segment the motorbike from background in both daytime and nighttime when the motorbike is arriving in the incoming traffic lane alone.

5. Conclusion

These preliminary results show that creating a traffic light triggering sensor based on computer image processing is very much a possibility. Further development on this project would include creating a classification system based on the trajectory estimation given by this algorithm. Additionally, motion tracking could perhaps be improved by using a more advanced tracking method such as the KLT tracker. [4]

References

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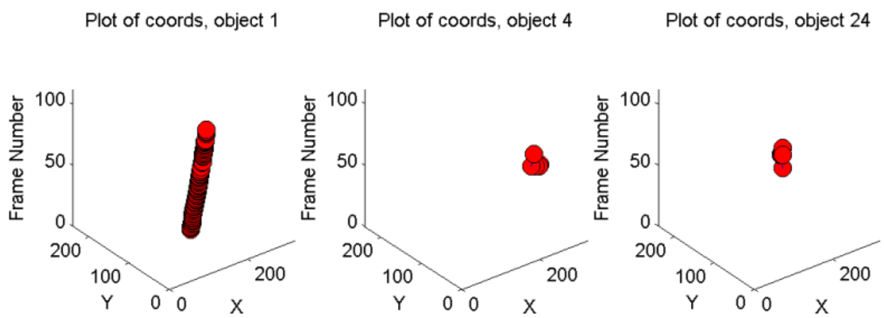
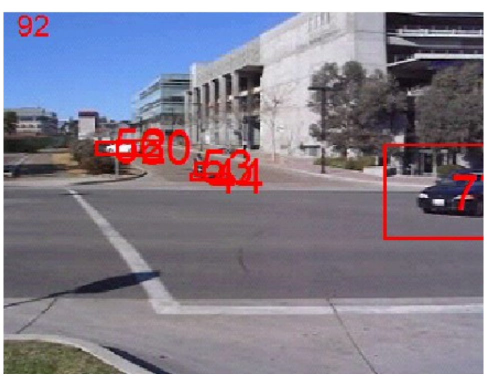
(a)



(b)

Figure 4. (a) At night time, incoming traffic objects are more easily tracked. (b) Plots of position against frames. Object 1 is the motorbike's headlight. Object 4 and 24 are fast moving cross-traffic objects that are short-lived.



(a)

(b)

Figure 5. (a) Daytime footage zoomed out. (b) The same frame zoomed in. In day time, objects are short lived compared to night time footage but the motorbike is detected.