

# Detecting and Counting Vehicles Using Adaptive Background Subtraction and Morphological Operators in Real Time Systems

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Received (2019-04-25)

Accepted (2019-07-22)

**Abstract:** Vehicle detection and classification of vehicles play an important role in decision making for the purpose of traffic control and management. This paper presents a novel approach of automating detecting and counting vehicles for traffic monitoring through the usage of background subtraction and morphological operators. We present adaptive background subtraction that is compatible with weather and lighting changes. Among the various challenges involved in the background modeling process, the challenge of overcoming lighting scene changes and dynamic background modeling are the most important issues. The basic architecture of our approach is done in 3 steps: 1- background subtraction 2- segmentation module 3- detection of objects and counting vehicles. We present an adaptive background at each frame after using binary motion mask to create instantaneous image of background. To remove noises we use morphological operators and then start to segment images, detect vehicles and count them. Algorithm is efficient and able to run in real-time. Some experimental results and conclusions are presented.

**Keywords:** Image processing, Vehicle detection, Machine vision, Background subtraction, Morphological operators.

**How to cite this article:**

Lida Shahmiri, Sajjad Tavassoli, Seyed Navid Hejazi Juybari. Detecting and Counting Vehicles Using Adaptive Background Subtraction and Morphological Operators in Real Time Systems. J. ADV COMP ENG TECHNOL, 5(4) Autumn 2019 : 213-220

## I. INTRODUCTION

Highway vehicle traffic management and planning are not common in developing countries. This is because they require integrated Intelligent Transport System (ITS) to collect vehicle data [1]. A robust and reliable monitoring system is needed to manage traffic. Detecting the flow in system monitoring seems important. Traffic monitoring systems have been explored in recent years because they can provide useful information such as current density, average traffic speed, and total vehicle traffic at constant intervals [2]-[3].

The main goal of image-based smart identification systems is to automatically

detect and track objects of interest from video screens, and then obtain the information needed by users. Image-based smart systems can effectively distinguish the foreground and background of a scene using reliable moving object detection technology. The foreground refers to objects that move after the image-based intelligent systems are initialized; objects that do not belong to the foreground are referred to as the background. Conversely, image-based intelligent systems track and identify objects in the foreground and can identify the behavioral patterns of moving objects. By analyzing background images, the systems can detect environmental changes in the monitoring field. In addition, existing image-based smart systems use



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increasingly higher image resolutions to retain more scene details, leading to increased hardware requirements for real-time identification and analysis of images. Therefore, the use of moving object detection technology that allows intelligent systems to identify the foreground or background can significantly reduce the amount of data that must be identified and analyzed by these systems. Many scholars have proposed various methods to detect moving objects. Moving object detection methods can be roughly divided into three types: temporal differencing, optical flow, and background subtraction, each of which is elaborated below. IN this paper background subtraction process, which is the difference of the reference frame and current frame is used for detection of moving object. The main objective of this paper is to present method for detecting vehicles which update the background automatically to be adaptive with illumination changes and whether condition.

In this paper, two basic morphological operations are investigated to remove noise and enhance the appearance of binary images. Mathematical morphology provides an approach to the processing of digital images that is based on the spatial structure of objects in a scene. However, morphological techniques for digital images rely only on the relative ordering of pixel values thus they are most suitable for binary or grayscale images. Noise is any unwanted information that contaminates an image. The digital image acquisition process, which converts an optical image into continuous electrical signal that is then sampled, is the primary source of noise. It is almost impossible to remove noise totally without distorting an image, but it is imperative that noise is reduced to a certain acceptable level for further analysis of the image [4]. The first method we describe is called temporal differencing, which uses the pixel differences of successive images to detect moving object [5]. Consecutive frame subtraction is an easy method and also works good in dynamic environment but it is not extraction moving object completely. Gaussian mixture model and water-shed are used in this type of method. Propose that where first the difference between two frames is calculated and then dividing it to moving area and background area [5].

For example Ssu-Wei Chen et al. [6] propose

a new tracking method that uses Three Temporal Difference (TTD) and the Gaussian Mixture Model (GMM) approach for object tracking. They used the GMM approach as the main tracking algorithm, with morphological and median filtering to remove noise. On the other hand, they used the TTD method to subtract successive images, also using morphological and median filters to remove noise. Due to TTD method tracking object incompletely, supporting the main algorithm GMM, the proposed method there is still room for improvement. They can replace the TTD method, fill the emptiness produced by the phenomenon of GMM, but the best algorithms in the future still need more testing to be able to get the perfect result. Next let us briefly review the optical flow. Unfortunately Optical flow is high time complexity and cannot meet the need of real time detection [7]. Optical flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and a scene. Optical flow can also be defined as the distribution of apparent velocities of movement of brightness pattern in an image. The concept of optical flow was introduced by the American psychologist James J. Gibson in the 1940s to describe the visual stimulus provided to animals moving through the world. For example in [8] Prof. Paygud and et al design detecting and tracking system ,the first step of paper is to pre-processing done on the video frame sequence. The second phase is segmenting the object using background subtraction method with the help of finding frame difference method which gives a better understanding of grouping objects. In the next phase the vehicle detection and tracking is done using the optical flow Algorithm .At last the moving object centroid is identified. These algorithms can also be extended for the use of real-time applications and object classification. The paper work could be extended using the identified centroid of the moving object the distance and velocity can be calculated which helps to find out the speed of the car from the video sequence. In Optical Flow Method, automatic feature extraction has been done by using clustering so that features are extracted from the current image by using x-mean cluster and classify extracted features points based on their estimated motion parameters. The segmented

region is labeled and labeling result characterize as moving object. Moreover it cannot be used for real time application without using some special hardware.

## II. LITERATURE SURVEY

Background subtraction is a superior method for detecting foreground object as well as to model the background. Many contributions can be found using different background subtraction techniques for a different aspect. Neha S. Sakpal et.al present a selective background subtraction technique was proposed to subtract only selective background which is unwanted in the image instead of subtracting the whole background. The proposed method worked on different input images which are then converted to grayscale and HSV images. Performance of the proposed method is calculated in terms of accuracy and speed [9]. Pal et.al have proposed code book background modeling and subtraction technique [10] to solve the challenges such as moving backgrounds and sudden and gradual illumination changes associated with the background modelling methods using the framework of codebook background modeling. They Separate background image using image segmentation function and then use pseudo background layer to model the background with a codebook for each pixel in the image. Chang et.al proposed the parallel design of background subtraction and template matching model [12]. They used this parallel approach to detect object and tracking system and improve the performance of tracking system. Lee et.al presented [13] low-cost background subtraction algorithm. In this algorithm, they used background sets with image-space and color-space reduction to reduced jittered and unsteady camera and color noise in the image to detect foreground from moving background. It also reduced the cost of the algorithm.

Mathematical morphological operations are commonly used as a tool in image processing for extracting image components that are useful in the representation and description of region shape.

It is been observed that the methods they have used for detection of moving objects without any extraction of dynamic feature of moving object.

Mathematical morphology provides an approach to the processing of digital images that is based on the spatial structure of objects in a scene. In [14] Aisha Ajmal and Ibrahim M. Hussain propose a novel and efficient algorithm based on image processing using vertically positioned camera for vehicle detection and classification according to their size. The algorithm is based on different techniques including Image differencing, edge detection and binary morphological process. Experiments are carried out over a wide range of vehicles road segments and camera positions. A success rate of around 85% is achieved in both vehicle detection and classification.

## III. SEGMENTATION

The first step in identifying vehicles is to segment the image to separate the background [15]. Different approaches exist in varying degrees of effectiveness in this topic. For being useful, segmentation methods should carefully remove cars from the background, be fast enough in real time, not sensitive to light and weather conditions. We used a distinct background subtraction method for fragmentation. Our segmentation technique consists of three tasks.

- A-fragmentation
- B-adaptive updates
- C-background extraction

For each sequence of our frames, we will differentiate the present frame from the background, which gives us a different image. A discrete image of the threshold is given to give a binary object mask. A binary object mask is a binary image that all the foreground pixels have a value of 1, and all pixels in the background are worth 0.



Fig. 1. Image in the current frame



Fig. 2. Background images of the present frame



Fig. 3. Differential picture

$curImgDift[i][j]=|CI_t[i][j]-CB_t[i][j]|$   
 $curImgDift[i][j]$  is a differential image of the current frame,  $CI_t[i][j]$  is the current frame and  $CB_t[i][j]$  is the current background.

$$BM[i][j]=\frac{\sum_{m=1}^N pri\ Image_m[i][j]}{N} \quad (1)$$

$BM[i][j]$  is the first image of the background to get an average of the pixels of several images and get this image as a background. By taking these calculations, we obtained about 100 images of

the original background. To make the difference image we subtract background and foreground, the subtractive image must be thresholded.

$$E_m[i][j]=\begin{cases} 0 & ImgDif_m[i][j] \leq threshold \\ 1 & ImgDif_m[i][j] > threshold \end{cases} \quad (2)$$

$ImgDifm[i][j]$  is a differential image. And  $Em[i][j]$  is the binary mask of the object. As you see in the formula, if the difference image is smaller than the threshold, then the mask moves the value of 0 and if the difference is greater than the threshold, then the value of our mask is 1.



Fig. 4. Binary image obtained from the difference (after the thresholding)

#### IV. ADAPTIVE UPDATE SIMULATION

Our aim in this article is the algorithm we will present would be adaptive, if we want to differentiate the image in the same way from the constant background, it is no longer sensitive to changes in light or climate, and unfortunately has a shadow and a ghost in a different image. For this reason, the background must be updated and changed over time as frames move forward.

We update the background by taking into account the average of the current background and the frame in the movie sequence. However, the current image also includes background objects. Object binary mask is used to detect the foreground pixel from the background pixel. The mask object acts as a function and decides which sample is used to update to define a motion mask, we use the background subtraction and the frame subtraction.

$$\Omega_n = M_n^B \& M_n^F; \quad (3)$$

Where  $\Omega_n$  is a motion mask and  $M_n^B$  is the difference between the present frame and the background.  $M_n^F$  Is the difference between two consecutive frames of the video.

$$M_n^B = \begin{cases} 1 & \text{if } |F_n(i, j) - B_c(i, j)| > \varepsilon_B \\ 0 & \text{else} \end{cases} \quad (4)$$

$$M_n^F = \begin{cases} 1 & \text{if } |F_n(i, j) - F_{n-1}(i, j)| > \varepsilon_F \\ 0 & \text{else} \end{cases} \quad (5)$$

$$IB_n[i][j] = \begin{cases} F_n(i, j) & \text{if } \Omega_n(i, j) = 0 \\ B_c(i, j) & \text{if } \Omega_n(i, j) = 1 \end{cases} \quad (6)$$

The result of this equation is an instantaneous image that uses a motion mask that is used to divide the current frame from the background and the difference of the current frame from the previous frame. As you see in the formula above, the mask acts like an input function and when the mask is 0, the current background takes up the current value of the current frame and when the background is 1, it will get the value from the previous background.



Fig. 5. An instant background

As you can see in the "Fig. 5," because of the fact that the image is not completely detected in binary images, the image is shadowed by vehicles. In order to obtain a complete object, we can use morphological operators and improve the image.

## V. EXTRACT THE BACKGROUND

After obtaining this instant background using one of the updates in the background contrast, we will update the background image. The present background is a set of the instantaneous background weights and the background of the previous frame.

$$CB_{t+1}[i][j] = a * IB_n[i][j] + (1 - a) * CB_t[i][j] \quad (7)$$



Fig. 6. The present background

## VI. MORPHOLOGICAL OPERATOR

One of the most important stages in image processing is the formation of morphology. In this section, as explained above, we use Morphological Operators to improve the image and eliminate image noise. Morphological operators which I use to improve the subtracted image in this article are in order:

### CLOSE OPERATOR

The operation of the close operator on the binary image will cause the small cavities of

the image to be filled. An example below is the implementation of this operator.



Fig.8. A differential image using close operator

### IMFILL OPERATOR

This operator allows you to fill in the identified holes. An example below is an example of this operator in the implementation. [10].



Fig. 9. A differential image using Imfill operator

We use these operators that are best suited to other operators and we give the best answer.

## VII. THRESHOLDING

Thresholding is done to separate the background pixels from the foreground. In order to have a better segmentation, it is better to have adaptive threshold, since brightness changes will also change the threshold value. For the threshold, we first began by playing with the threshold values, which is a kind of fixed threshold for our work and was not correct. For our threshold, we have 5 algorithms for four dataset that we have.

- 1-medium gray levels
- 2-The method of two peaks

- 3-Edge pixels method
4. Iterative Threshold Method
- 5 Percentage of Black Pixels

The best result for these four cases for detecting moving objects from the repeating threshold algorithm was Iterative Threshold Method. The corresponding code is shown below.

```
% calculate mean gray level
[rmax cmax] = size (image);
T = 0;
T = sum (sum (image));
T = T / (rmax * cmax)
Tnew = -1;
while round (T) ~= round (Tnew)% not equal
if tnew ~= -1
T = Tnew;
end
Tlow
sum (image (find (image <t)))) / max (size
(find (image <t)))
Thigh =
Sum (image (find (image> = T)))) / max (size
(find (image> = T)))
Tnew = (Tlow + Thigh) / 2
end .
```

The method of work, as you see in the code, is first define a gray level average of the corresponding image and define it as threshold, and then, as long as the value of the threshold is defined by the value of Tnew is different, and if the Tnew variable is opposed to -1, then we define the Tlow and Thigh variables and define the mean as threshold.

## VIII. DETECTION OF OBJECTS AND COUNTING

After applying the morphological operators and as we see in the screenshots, moving objects that are the same ones turn into closed areas of pixels that have a value of 1. To separate them from the foreground and specify them as vehicles we use tagging algorithm of connected components. This algorithm is based on the theory of graphs, which is a subset of unique connected components with an exploded label. The use of the binding of connected components in the machine vision is to detect connected regions in binary images.

This method is very simple and fast to implement. The algorithm processes are as follows.

1. Start from the first pixel of the image
2. If this pixel is foreground and has not already been tagged, then that pixel is tagged and placed as the first component in the queue. And it goes to step 3. If this pixel is the background pixel, the second step is to the next pixel applies.
3. An element of the queue and looking at its neighbors. If the neighboring pixel is a pixel of the foreground and not already labeled, it will be tagged and queued. We continue the Step three until there aren't in the queue.
4. Go to step two for the next pixel.

Note that pixels are labeled before the process queue. After tagging the components for each component of each vehicle, these sets are rectangular for each object set. After tagging and identifying the connected components, we consider each component as a car and using the Moore neighborhood method, the outer boundaries trace known objects that are the same cars and are identified by numbers, and we count the number of traceable objects.

## IX. RESULTS AND DISCUSSION

Good Detection is defined as the probability of the selective background pixels not being classified as either foreground or background. This term is represented as TP (True Positive). The value of this term should be high, as less selective background pixels will be classified as foreground or background pixels; the number of true negatives (TN), which counts the number of correctly not detected selective background pixels. Thus FP means, selective background pixels (P) from non-selective background area (E, false area selected). And similarly FN means, non-selective background pixel (N) area is false i.e. selective background area (F).

Accuracy:

$$p = \frac{TP}{TP + FP} \quad (8)$$

Recovery criterion:

$$r = \frac{TP}{TP + FN} \quad (9)$$

Harmonic Average:

$$F = \frac{2 * p * r}{p + r} \quad (10)$$

Several experiments have been carried out after the implementation of this method in the MATLAB software.

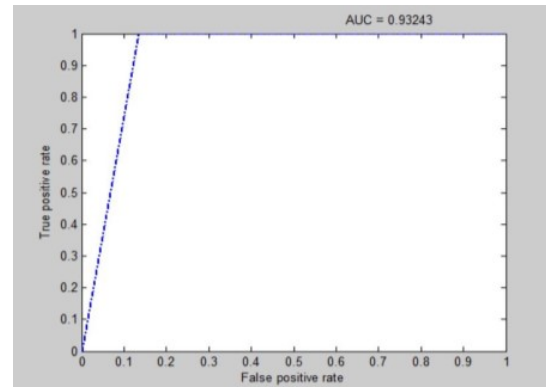


Fig. 7. Accuracy

In this proposed method Accuracy is about 0.93, Recovery criterion is about 0.95 and Harmonic Average is about 0.941359. The module has proven to be reliable, efficient. The average computation time of our approach including detection and counting is 20ms per frame, which is four times faster than the sensor update rate.

## X. CONCLUSION

In this section, we will summarize and conclude the work done in this article, and will be followed by future actions and activities. In the background subtraction method, each frame is a difference of the present frame and the background and a distinctive image is mapped to identify the moving objects. In this article, given purpose is used to detect the vehicle and the background scene is on outer space And it is constantly changing, it has been attempted to change the background as background lighting. It is also possible to use a morphological operator to eliminate noise and to form a more accurate form of the car. After the algorithm is presented the corresponding method is implemented, a series of experiments between the proposed method

and other methods are carried out. Fortunately, we reached the desired result in accuracy and speed the above method is to detect cars and unfortunately in our country there are lines that are for cars, only cars do not cross and people pass it. My suggestion is to provide a solution for detecting a car and separating it from pedestrians using a background subtraction algorithm. The above algorithm is considered for fixed cameras. For a wider view, the next suggestion is to use dynamic cameras to detect a car. The above algorithm is considered for two-dimensional cameras. The next proposal presents an algorithm using the background algorithm for 3D cameras.

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