ON ROAD VEHICLE/OBJECT DETECTION AND TRACKING USING TEMPLATE

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Abstract

Vehicle tracking and detection plays an important role in traffic surveillance, still a crucial task in many applications. Till now, there is no standard method developed. Template matching is one of the methods used for vehicle detection and tracking. There are several researchers and developers worked on this area. Robust and reliable vehicle detection is a critical step of vehicle recognition. This paper presents a review of recent template matching methods for detection and tracking of vehicle. Our focus is on systems where the camera is mounted on the vehicle and being fixed such as in traffic/driveway monitoring systems. We discuss the general template matching followed by problem of on-road vehicle detection using template matching. Also, discuss vehicle recognition through number plate and ways. Finally, we present a critical overview of the methods discussed, and we assess their potential for future deployment, and we present directions for future research.

***Keywords*:** Template matching; vehicle detection and tracking; correlation.

1. Introduction

Computer vision is the science and technology of machines that see. As a scientific discipline, computer vision is concerned with the theory behind artificial systems that extract information from images. The image data can take many forms, such as video sequences, views from multiple cameras, or multi-dimensional data from a medical scanner. Computer vision is closely related to the study of biological vision. The field of biological vision studies and models the physiological processes behind visual perception in humans and other animals. Computer vision, on the other hand, studies and describes the processes implemented in software and hardware behind artificial vision systems. Interdisciplinary exchange between biological and computer vision has proven fruitful for both fields.

The classical problem in computer vision, image processing, and machine vision is that of determining whether or not the image data contains some specific object, feature, or activity. This task can normally be solved robustly and without effort by a human, but is still not satisfactorily solved in computer vision for the general case: arbitrary objects in arbitrary situations. The existing methods for dealing with this problem can at best solve it only for specific objects, such as simple geometric objects (e.g., polyhedral), human faces, printed or hand-written characters, or vehicles, and in specific situations, typically described in terms of well-defined illumination, background, and pose of the object relative to the camera.

In the *template matching* approach, researchers create a library of possible visual patterns of vehicles (objects) to seek similarity between a segment of the actual video frame and a library image, or *template*. Once such similarity is found, the frame part is classified as a of vehicles (objects) image. Although this approach can be useful in some circumstances, but this approach not very efficient because it requires the creation of a huge library of templates.

There are various methods are applied for the above said. Template matching is one the way for performing operations like: object recognition, identification or classification, and detection. There are various literature are available for template matching method but they vary from application to application. There is no standard method developed yet.

Template matching is conceptually a simple process. We need to match a template to an image where the template is a subimage that contains the shape we are trying to find. Accordingly, we centre the template on an image point and count up how many points in the template matched those in the image. The procedure is repeated for the entire image, and the point that led to best match, the maximum count, is defined to be the point where the shape (given by the template) lie within the image. If standard deviation of the template image compared to the source image is small enough, template matching may be used. Templates are most often used to identify printed characters, numbers, and other small, simple objects. Template matching is performed on either bi-level image (black and white) or grey level image depends on the application. For example, for character recognition and number plate of vehicle bi-level image are used while for vehicle or object recognition grey level image is used.

Formally, template matching can be defined as a method of parameter estimation. The parameters define the position (and pose) of the template. We can define a template as a discrete function of $T_{x,y}$. Template matching uses a similarity criterion for locating an object, where one common method calculates a correlation coefficient using the following equation:

$$\rho = \frac{\sum_x \sum_y (A_{xy} - \bar{A})(B_{xy} - \bar{B})}{\sqrt{\left(\sum_x \sum_y (A_{xy} - \bar{A})^2\right)\left(\sum_x \sum_y (B_{xy} - \bar{B})^2\right)}} \quad (1)$$

where A and B are image matrices, $\bar{A}$ and $\bar{B}$ are the 2-dimensional means of the respective image metrices, and (x, y) are the spatial coordinates within *A* and *B*[Garboczi et al. 1999]. This correlation coefficient closely resembles a traditional statistical correlation, with the difference being that the traditional method is calculated in one dimension instead of two dimensions. A high correlation coefficient in a pixel-by-pixel comparison between the template and the region of interest (ROI) indicates a good match.

This “cross-correlation’’ yields a result only if the integral is computed over the whole area *G*. In the discrete case, this takes the form

$$R(i,j) = \sum_m \sum_n f(i+m, j+n) * g(m,n), \quad (2)$$

if the variation in the energy of the image *f* can be ignored. Otherwise the normalized cross-correlation has to be used:

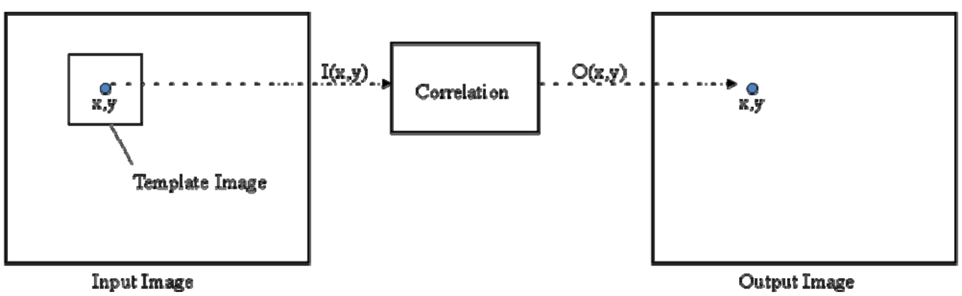

Fig.1: Example of Template matching

$$R(i,j) = \sum_m \sum_n f(i+m, j+n) * g(m,n) \Big/ \sqrt{\sum_m \sum_n f(i+m, j+n)^2} \quad (3)$$

It takes the same amount of computing time for any $g \in G$, whereas the computation of the other two measures can be halted as soon as the *misregistration*

$$\sum_m \sum_n |f(i,j) - g(i-m, j-n)| \quad (4)$$

Let us consider that each pixel in the image $I_{x,y}$ is corrupted by additive Gaussian noise. This noise has a mean value of zero and the (unknown) standard deviation is σ. Thus the probability that a point in the template placed at coordinate (i, j) matches the corresponding position (x, y) Є w is given by the normal distribution.

Since the noise affecting each pixel is independent, the probability that the template is at position (i, j) is the combined probability of each pixel that the template covers. That is,

$$L_{i,j} = \prod_{(x,y)\in w} p_{i,j}(x,y) \quad (5)$$

$$L_{i,j} = \left(\frac{1}{\sqrt{2\pi}\sigma}\right)^{s} e^{-\frac{1}{2}\sum_{(x,y)\in w}\left(\frac{I_{x+i,y+j} - T_{x,y}}{\sigma}\right)^2} \quad (6)$$

If the camera is located at some fixed point there may be a chance that the object is reduced in size compare to its original size. A two tier hierarchal representation of images for each object is created, for reducing the set of images to match against. A clustering is used is reduced to the number of blobs of extracting area of interest[Cole and Austin, 2004].

2. Outline of the paper

The paper is followed in given sequence. The section 1: define the computer vision, vehicle detection and recognition, temple matching. Section 3: discuss about various template matching methods. Section 4: discussion about their drawbacks, some of the results, possible future research. In last, references are given.

Preprocessing

Video acquired from the may contain some noise due to weather, atmosphere, illumination, camera position also. [Bo, 2007] proposed a smoothing template method for reducing the region of interest, which reduces the computation time and computation cost also.

3. Template –based vehicle (object) detection

If a template describing a specific object is available, object detection becomes a process of matching features between the template and the image sequence under analysis. Object detection with an exact match is generally computationally expensive and the quality of matching depends on the details and the degree of precision provided by the object template. There are two types of object template matching, fixed and deformable template matching.

3.1. *Fixed template matching*

Fixed templates are useful when object shapes do not change with respect to the viewing angle of the camera. Two major techniques have been used in fix template matching.

3.1.1. *Image subtraction*

In this technique, the template position is determined from minimizing the distance function between the template and various positions in the image. Although image subtraction techniques require less computation time than the following correlation techniques, they perform well in restricted environments where imaging conditions, such as image intensity and viewing angles between the template and images containing this template are the same. A template matching[Chang et al., 2003] is used to find out the vehicle candidate[Shen 2007]. The template matching is used to find the category to which the tracked object belongs and to find its original image[Baskaran and Dhavachelvan, 2010]. A two-stage template-based method is used to detect people in widely varying thermal imagery. In first stage location was obtained of the object; in second stage, Adaboost classifier with adaptive filter is used to classify the object[Davis and Keck, 2005].

3.1.2. *Correlation*

Matching by correlation utilizes the position of the normalized cross-correlation peak between a template and an image to locate the best match. This technique is generally immune to noise and illumination effects in the images, but suffers from high computational complexity caused by summations over the entire template. Point correlation can reduce the computational complexity to a small set of carefully chosen points for the summations. [Krattenthaler, 1994]

A feature correlation template method is used to recognize the object from remote sensing images [Cucchiara et al., 2000; Zhang and Zhou, 2004]. A cross correlation method is used for detecting headlight pairs of vehicle [Cucchiara et al., 2000]. A search method on the basis of the dynamic programming (DP) technique in image processing is used for pattern matching. The method is based on template matching between a template image and an input image[Muramatsu and Kobayashi, 1998]. A two step temple matching is used to count and classify the vehicles from KOMPSAT EOC Imagery[Hee et al., 2005].

A system for automatic detection and recognition of vehicle license plates using template matching, genetic algorithms and neural networks is proposed by [Karungaru et al., 2009]. In the character recognition part, we combine two methods into a hybrid system. In the first method, we train neural networks to recognize the characters and in the second method, use template matching. Author's proposed a tracking method which is based on characteristics of both traffic scene and vehicle[Chang et al. 2006]. Author's proposed a method for vehicle identification which is a combining of knowledge-based and learning-based method. During vehicle tracking, templates are dynamically created on-line, tracking window is adaptively adjusted with motion estimation, and confidence is determined for tracked vehicle[Liu et al., 2007].

Tracking of detected vehicle is performed by template matching algorithm [Zu, 2006; Kim et al., 2005]. The object (vehicle) classification uses two new techniques − color contour based matching and gradient based matching[Ambardekar, 2007]. A novel tracker for semi-automatic extraction of ribbon road centerlines from high resolution remotely sensed imagery is proposed. Actually, our approach is an integration of least squares profile matching and least squares rectangular template matching. After initialization, a road template model is built which is composed of two parts: a profile perpendicular to the road axis, and some rectangular templates of strips of road marks or strips of vegetation parallel to road moving direction[Xiangguo et al., 2008].

A probabilistic algorithm for visual tracking that incorporates robust template matching and incremental subspace update. There are two template matching methods used in the tracker: one is robust to small perturbation and the other to background clutter. Each method yields a probability of matching[Mei et al. 2007]. Author's proposed an improved one based on Gabor features, which contains three consecutive stages: vehicle segmentation, Gabor features extraction and template matching[Zhao et al., 2005]. Author's proposed a probabilistic algorithm for tracking and recognition that incorporates robust template matching and incremental subspace update. There are two template matching methods used in the tracker: one is robust to small perturbation and the other to background clutter. Each method yields a probability of matching. The templates are represented using mixed probabilities and updated when the appearance models cannot adequately represent the variations in object appearance[Mei et al., 2007]).

Author's proposed a template matching of vehicle logo for recognizing the type of vehicle instead of conventional way (i.e. shape, size, color, axle or head lights of the vehicle etc.). The vehicle logo is unique mark of vehicle type (both make and model)[Wang et al., 2007].The weight feature based hierarchical template evaluation method is used to detect license number plate for surveillance purpose[Mi and Young, 2003].

For recognizing the cars in video, number plate recognition is also useful. For searching number plate template images normalized cross correlation (NCC) is used. Scale invariant feature transform (SIFT) is used to recognize the cars in traffic video. The accuracy achieved by this method is 89.5% [Dlagnekov and Belongie, 2005]. A template matching feature correlator is used to detect object[Tippetts, 2008]. Vehicle detection and hypothesis generation is performed using a template correlation technique[Ferryman et al., 1998]. A statistical based template matching is used for recognition of plate characters[Ozbay and Ercelebi, 2005]. An algorithm for a rotation invariant template matching method based on the combination of the projection method and Zernike moments is proposed[Choi and Kim, 2002]. Vehicle detection and hypothesis generation is performed using a template correlation technique[Ferryman et al., 1998]. This study presented a novel method of identifying and recognizing license plates based on the morphology and template matching [Kasaei et al., 2009].

3.1.3. Normalized Correlation

However, in unipolar images (with only positive intensity values) this correlation formula can give high response in a region even though the region does not fit the template at all. This is due to the fact that regions with high intensity yield higher response since no normalization is performed.

A couple of different normalized correlation formulas are common. While the first only normalizes the correlation with the norm of the region and the template the second also subtracts the mean intensity value from the image region, μ_I, and the template, μ_t.

$$C(x,y) = \frac{\sum\sum_{\alpha,\beta} I(x+\alpha, y+\beta)\, t(\alpha,\beta)}{\sum\sum_{\alpha,\beta}(I^2(x+\alpha, y+\beta) - \mu_I)^2 \sum\sum_{\alpha,\beta}(t(\alpha,\beta) - \mu_t)^2} \quad (7)$$

$$C(x,y) = \frac{\sum\sum_{\alpha,\beta}(I(x+\alpha, y+\beta) - \mu_I)(t(\alpha,\beta) - \mu_t)}{\sum\sum_{\alpha,\beta}(I^2(x+\alpha, y+\beta) - \mu_I)^2 \sum\sum_{\alpha,\beta}(t(\alpha,\beta) - \mu_t)^2} \quad (8)$$

The bike is detected by M-HD template matching[Zheng et al., 2002]. Vehicle tracking by template matching calculating the normalized cross correlation is performed on consecutive image pairs and is based on the vehicle detection in the first image of an image sequence. For each vehicle detected in the first image, a template image is produced. Then, a search area for each detected vehicle is defined in the second image of the exposure sequence. Within this search area the normalized cross correlation between the template image and the second image is calculated for all 3 channels of the RGB images. The calculated correlation value gives a score for a possible hit. With this method we are able to track vehicles over a whole image sequence (burst), whereas a special evaluation algorithm that validates matches in velocity space reduces false alarms in vehicle detections and mismatched vehicles in template matching.

3.2. Deformable template matching

Deformable template matching approaches are more suitable for cases where objects vary due to rigid and non-rigid deformations. These variations can be caused by either the deformation of the object per se or just by different object pose relative to the camera. Because of the deformable nature of objects in most video, deformable models are more appealing in tracking tasks.

In this approach, a template is represented as a bitmap describing the characteristic contour/edges of an object shape. A probabilistic transformation on the prototype contour is applied to deform the template to fit salient edges in the input image. An objective function with transformation parameters which alter the shape of the template is formulated reflecting the cost of such transformations. The objective function is minimized by iteratively updating the transformation parameters to best match the object [Jain et al., 1996]. The most important application of deformable template matching techniques is motion detection of objects in video frames which we will review in the following section. [Sclaroff and Liu, 2001; Zhong et al.,2000]

The object (vehicle) classification uses two new techniques − color contour based matching and gradient based matching[Ambardekar, 2007]. The roads and their orientation have been detected because they are vital evidence as the Region of Interesting of Vehicle Location[Pantavungkour and Shibasaki, 2002]. To detect lane robustly at real time, Fast Fourier Transform (fft) based template matching technique is applied. An algorithm for a rotation invariant template matching method based on the combination of the projection method and Zernike moments is proposed[Choi and Kim, 2002]. The correct number and vehicle length of street-parking vehicles is obtained by using the width of two templates for matching and fuse the two results together. First, a template with the length of approximated threshold of vehicle length, V Lth, is used for detecting street parking vehicles. After that, a template with shorter length is used to determine the vehicle length[Zhu et al., 2003].

An artificial immune approach is presented to extract vehicle targets from high resolution panchromatic satellite imagery. This approach uses the antibody network concept inspired from the immune system to learn a set of templates called antibodies for vehicle detection. Based on learned template antibodies, an immune detection strategy is proposed to locate vehicle targets in satellite imagery, and a morphology based preprocessing algorithm is also developed to generate candidate template antibodies[Zheng and Li, 2007].

3.2.1 Histogram template matching

Another potential template-matching method that is also being considered in the larger scope of this research project uses an average histogram signature template [Bertozzi and Broggi, 1998]. A varying brightness and contrast histogram based template is used for object detection[SCHRIDER, 2008]. Author’s proposed a similarity based method for template matching for recognizing the car in both day and night light[Thiang et al., 2001]. Its first approaches to detect vehicles in the blind spot of a driving car[Krips et al., 2003].

3.3 Stereo Vision

Epipolar geometry describes the geometry of two views, i.e., stereo vision. Given a single image, the 3D point corresponding to a point in the image plane must lie on a straight line passing through the camera centre and the image point. Because of the loss of one dimension when a 3D point is projected onto an image plane, it is impossible to reconstruct the world coordinates of that point from a single image.

However, with two images of the same scene taken from different angles, the 3D point can be calculated by determining the intersection between the two straight lines passing through respective camera centers and image points. One such line projected onto another image plane of a camera at a different view point is known as the epipolar line of that image point. The epipole is the point in one of the images where the camera centre of the other image is projected. Another way to put it is that the epipolar points are the intersections between the two image planes and a line passing through the two camera centers.

A specific navigation and positioning method, called elastic template matching, in an outdoor environment. Elastic template matching was developed by Balkenius and Kopp of Lund University Cognitive Science. They built a robot named Polucs [Balkenius & Kopp, 1997], which used elastic template matching for indoor navigation.

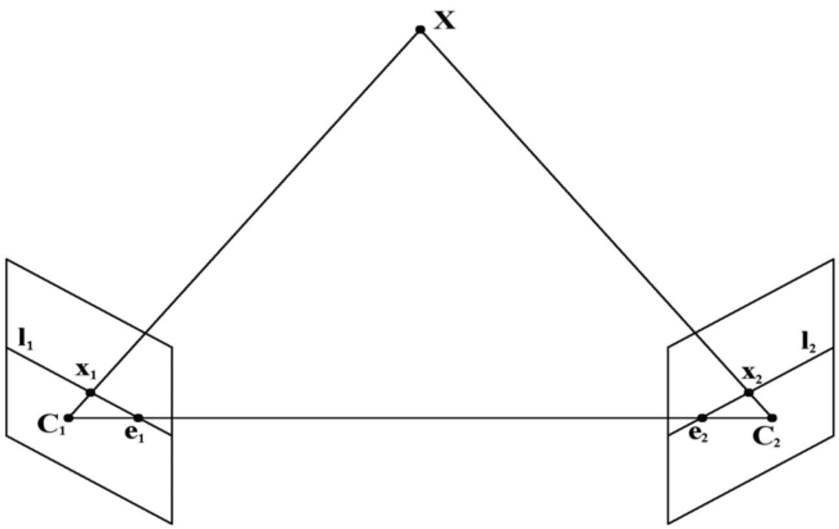

Fig. 2. The projection of a 3D point *X* onto two image planes. The camera centers *C*1, *C*2, image coordinates *x*1, *x*2, epipolar lines *l*1, *l*2 and epipoles *e*1, *e*2.

Elastic template matching matched even better in an outdoor environment. If the system can use reference points far away, a higher localization certainly will be present. Elastic template matching works better in a messy environment [Balkenius, 1998]. An outdoor environment has few clean contours and many small objects which result in a very messy environment. This suit the matching method cause it could extract more features to use when matching. But to be able to extract the feature a higher resolution of the picture must be used.

Chamfer matching is a special case of template matching. The templates in this case are binary arrays which take on the value 1 at a silhouette edge and 0 elsewhere. The template *t* is shifted over an edge mapped-image *E* and for each position the distance metric $D_{chamfer}$ is computed, which is defined at location *l* as:

$$D_{chamfer}(t, l) = \frac{1}{|t|} \sum_{k \in t} DT(k + l) \qquad (9)$$

where distance transform *DT* is an image that, for each pixel, that contains the distance to the nearest edge pixel in *E*. Since *DT* takes the value 0 on edges, the lowest theoretical value for $D_{chamfer}$ is 0 and occurs when a template perfectly matches a patch in the *E*. The optimum template values for *t* and *l* are given by iterating over all pairs: (,) arg min (,)

$$(t_0, l_0) = \arg_{t \in T} \min_{l \in L} D_{chamfer}(t, l) \qquad (10)$$

for template database *T* and the set of all pixel positions *L*.

A multivehicle detection system based on stereo vision has been developed for better accuracy and robustness. This system utilizes morphological filter, feature detector, template matching, and epipolar constraint techniques in order to detect the corresponding pairs of vehicles[Hwang et al., 2009].

Our cities are facing congestion problem. It can be avoided upto some extent by prioritizing the traffic signal at intersections. To control effectively the control signal, it is necessary to identify the public transport vehicle. A temple matching method is used to identify the bus route number[Yamaguchi et al., 1999]. The traffic signs have specific color information like red border for warning and restricting signs or blue background for information signs. However in images obtained by camera mounted in the car or at some fixed location color information was changed due to lighting and weather conditions such as dark illumination, rainy and foggy weather etc. Structure of information signs is differs from structure of warning and restricting signs. The meaning of traffic sign lies in shape of symbols inside of it. Firstly, the shape of the sign is classified using background and shape histogram. Secondly, the template matching is used to recognizing the road sign[Andrey and Hyun, 2006]. The phase only correlation and template matching is used to recognize the road sign[Yuyama and Mitsuhashi, 2008]. A temporally integrated template matching technique based on the class-specific discriminative local region representation of an image is adopted[Ruta et al., 2008]. An automated Traffic sign recognition system allowing an invariance localization to changes in position, scale, rotation, weather conditions, partial occlusion, and the presence of other objects of the same color[Varan et al., 2007].

Author's proposed knowledge-guided boundary following and template matching for automatic vehicle identification[Lee et al., 1994]. A sensor platform with multi-modalities, consisting of a dual-panoramic peripheral vision system and a narrow field-of-view hyperspectral fovea is developed for real time moving target tracking[Tao and Zhigang, 2008].

There were various obstacles would be faced by the drivers (vehicle) on road. Pedestrian is one of such obstacle on road. The position verification of pedestrian on road is calculated by template matching method. The position of the vehicle is achieved by the concept of Histogram Intersection, which tells how many of the pixels in the model histogram are found in the image[Chung et al., 2003].

The roads and their orientation have been detected because they are vital evidence as the Region of Interesting of Vehicle Location[Pantavungkour and Shibasaki, 2002]. To detect lane robustly at real time, Fast Fourier Transform (fft) based template matching technique is applied. A shifting templates (eigendrops) one pixel at a time is used to detect rain drop[Kurihata et al., 2006].

4. Conclusion

However, this template matching method quickly fails by influence of disturbance, such as with illumination changes and rotation of the object. For example, a circumstance where template matching can fail is when real-world images acquired in outdoor settings are affected by the changes in sun location and cloud cover [4]. Template matching will also fail when the object in question is rotated within the image. This limitation is apparent when template matching is used to search text for a letter or word. When a letter is rotated, a low correlation coefficient is returned and the letter is not recognized as a match to the template letter.

Even if improvements are made concerning feature extraction, point matching and estimation of the fundamental matrix, the core problem still remains: points on vehicles move along their epipolar lines and are therefore impossible to reject as outliers. One alternative way to estimate the fundamental matrix would be to assume a forward translation and use the velocity from the vehicle's CAN bus along with the camera calibration matrices to calculate the estimate.

The edge based and the shadow based algorithms should be seen as two mature algorithms ready to use for rear-view vehicle detection in daylight. The edge based algorithm has been modified from the original article by Sun et al. [26] by, e.g., using local edge detection and from Wenner's approach [27] by introducing the top edge, symmetry and variance as additional vehicle cues. The shadow based algorithm, as opposed to the article by Tzomakas et al. [18], uses a row-by- row local estimation of the road intensity mean and standard deviation and interpolation to rows where no road points were extracted. Also, variance is used to reject ROIs.

The ultimate goal for a detection algorithm is ideally, but not very realistic, a PD(Positive detection) rate of 100% and none of the two algorithms are there. Still, two algorithms have been implemented that work well in good conditions and in the case of the edge based algorithm also in more difficult scenes. Yet, the most interesting statistics were those from the combination of the two algorithms with a PD rate of close to 90% even at distances up to as far as 100 m. Vehicle detection is a complex problem with a large number of parameters like illumination, poses, occlusion, etc. The way to go is therefore probably to combine different detection cues to improve robustness.

Not only on road is camera used for acquisition of vehicle video. Pantavungkour and Shibasaki used satellite image for automatic object detection on the road by using TLS image, high resolution Airborne Image which gives a promising result. Specially, the roads and their orientation have been detected because they are vital evidence as the Region of Interesting of Vehicle Location. The satellite image aspect of vehicle recognition is a costly affair.

The top edge was better aligned with the shadow based algorithm than with the edge based. This indicates that a fix aspect ratio works well when only detecting cars. Since the top edge is used to reject structures including a bottom and two side edges it should still be a part of the algorithm. But once detected, a ROI could possibly be better aligned using a fix aspect ratio. As it is now the vanishing point is fix for a certain camera calibration. An error will therefore be introduced when the road on which the vehicle is driving on is not flat. This leads to errors when estimating the allowed width and height of a vehicle at a certain distance from the camera and possibly to rejections of vehicles or approvals of non-vehicles. A dynamic, robust calculation of the vanishing point, e.g., using the Hough transform could prevent this. In addition, an algorithm detecting the road boundaries would help to decrease the number of Object detection (ODs).

We presented a critical survey of vision based on road vehicle detection system by template matching. The research activities underway worldwide, it is certain that this area will need lot of further exploration in near future.

Along with the increasing popularity of video on internet and versatility of video applications, availability, efficiency of usage and application automation of videos will heavily rely on object detection and tracking in videos. Although so much work has been done, it still seems impossible so far to have a generalized, robust, accurate and real-time approach that will apply to all scenarios. This will require a combination of multiple complicated methods to cover all of the difficulties, such as noisy background, moving camera or observer, bad shooting conditions, object occlusions, etc. Of course, this will make it even more time consuming. But that does not mean nothing has been achieved.

In our opinion, research may go more directions, each targeting on some specific applications. Some reliable assumption can always be made in a specific case, and that will make the object detection and tracking problem much more simplified. More and more specific cases will be conquered, and more and more good application products will appear. As the computing power keeps increasing and network keeps developing, more complex problem may become solvable.

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