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Vision based inter-vehicle distance estimation with extended outlier correspondence

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***Abstract*—In this paper, we propose a vision-based robust vehicle distance estimation algorithm that supports motorists to rapidly perceive relative distance of oncoming and passing vehicles thereby minimizing the risk of hazardous circumstances.**

And, as it is expected, the silhouettes of background stationary objects may appear in the motion scene, which pop-up due to motion of the camera,which is mounted on dashboard of the host vehicle.

To avoid the effect of false positive detection of stationary objects and to determine the ego motion a new Morphological Strip Matching Algorithm and Recursive Stencil Mapping Algorithm(MSM-RSMA)is proposed. A new series of stencils are created where non-stationary objects are taken off after detecting stationary objects by applying a shape matching technique to each image strip pair. Then the vertical shift is estimated recursively with new stencils with identified stationary background objects. Finally, relative comparison of known templates are used to estimate the distance, which is further certified by value obtained for vertical shift.

We apply analysis of relative dimensions of bounding box of the detected vehicle with relevant templates to calculate the relative distance. We prove that our method is capable of providing a comparatively fast distance estimation while keeping its robustness in different environments changes.

Keywords : Image Correspondence, Contour Detection, Vehicle Tracking, Distance Calculation

I. INTRODUCTION

According to "Global status report on road safety 2013", approximately 1.25 million people die on the worldwide roads. Half of the deaths occur among vulnerable road users like motorcyclists, pedestrians and cyclists. By 2030 road crashes are predicted to increase by 65% and it is the fifth leading cause of death. Any hazard alarming system deals with high response rate may assist to reduce these deaths and severe injuries caused by on road accidents. It should rapidly identify critical situations and provide the information to the driver or vehicle's safety mechanism to react suddenly, avoid or minimize the effect of the crash. Vehicle distance estimation is a prominent subset of researches on road safety. The initial step of it is vehicle detection. In vehicle detection, searching the whole image to locate vehicles, as it is proposed in most of articles [3], [7], [8], [11],is not really applicable in real time applications. A localized or simplified search method is more appropriate. Most of works on vehicle detection include tracking motion and vehicle verification which require a high computational load, making the model infeasible for online applications.

In the literature, the motion detection process is given in two forms as motion-based and feature-based detection. In motion-based methods ,the optical flow fields from a moving vehicle is calculated by matching pixels or feature points between two image frames of the video[2],[3],[5]. Sparse optic flow methods track specific features in two frames like corners [3] and colour blobs [5]. Segmentation is then performed by clustering detected flows.

On the other hand feature-based techniques [7], [8], [9], [11] use some specific features of the target object, in vehicle detection it is the rear view of passing or the front view of oncoming vehicle. Compared to motion-based models , feature-based models are computationally inexpensive. However, they suffer the problem of false detection due to object edges mixed with other surrounding edges in the background, and occlusions made by other vehicles. In our approach we propose to use the changes in contours to detect moving vehicles and another feature based approach to estimate the relative distance form the host vehicle.

II. RELATED WORK

In [6] Chen *et al* proposed to use multiple features of vehicles such as corner, edge, gradient, vehicle symmetry property to detect the vehicles and their relative distance from the host vehicle. They used matching technique to detect vehicle's width by using bottom edge of the vehicle, which is less likely to the occlusions, since it is always open in the frontal view of the host vehicle. They used Harris corner detection and Gaussian Mixture Model threshold to detect corners and edges of the vehicles. In addition to that it was proposed to use symmetric property of the vehicle to confirm their judgements on detected vehicles. Distance is obtained with calculated width-to-height ratio of vehicles with that of of predetermined templates.

In [13] Zhao *et al* proposed a vision-based relative vehicle distance estimation method. They used synchronized binocular clues and edges to certify the outcome of matching. In addition to the vehicle features they applied Hough Transformation for lane detection which was later coupled to their vehicle distance algorithm. These algorithms are computationally intensive which makes them infeasible to use in real time applications.

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III. Our Proposed Method

We prove that with added feature based techniques, the geometric differences of silhouette in consecutive frames of the video can be used to find not only the relative distance of the vehicles but the ego motion in an efficient manner, which is computationally inexpensive compared to the methods previously proposed. The simple morphological operation (scaling and translation) is interactively applied to one of the two frames when the comparison is taken place and silhouettes of the non stationary object (vehicles) are superimposed each other within the series of selected frames, thereby making its motion effect invariant to the subsequent procedures. . Here, for the sake of simplicity, it is assumed that camera rotation is insignificant, (which is justifiable with two adjacent(sampled) frames).

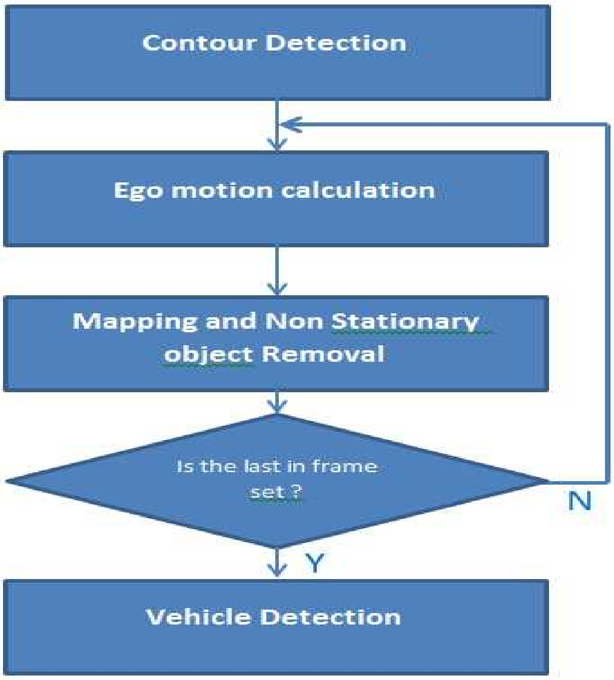

Fig. 1. silhouettes of moving objects are removed and added to separate motion scene)

Fig. 2. after previous iteration of ego motion estimation, only the superimposed silhouettes of non- stationary objects are visible in the stencil

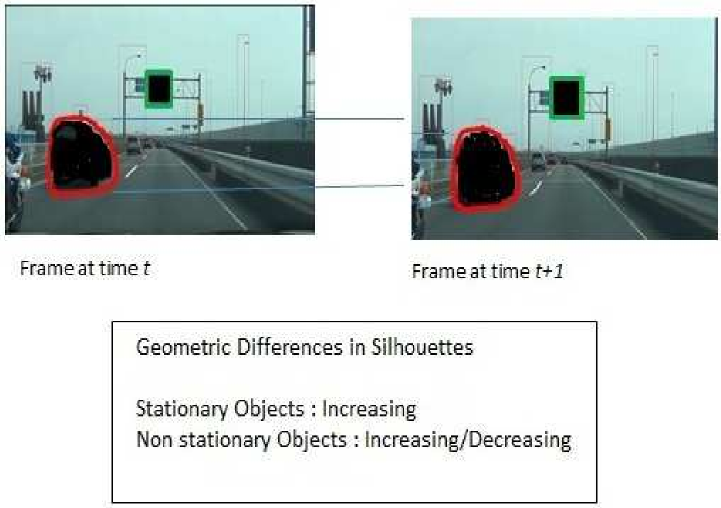

Fig. 3. Contour difference to track objects

Our algorithm follows an active contour approach in the view of improved efficiency since active contours make effective use of specific prior information about objects which make algorithm inherently efficient. Instead of processing the entire image active contours apply image processing on selectively region of the image. However the motion scene may include the contours of stationary objects related to the background as sign boards and road marks due to changes occur in geometry of those contours when camera moves towards them, which should be avoided in the motion scene.

Our method is in three fold, initially we find the contours of objects in the scene taking two sample frames at a time , and we match the geographic differences of them to track the object boundaries. At this stage we get the contours of real and false objects, secondly we make the stencils of two frames removing the objects detected (some erroneously detected stationary background objects are also removed). Thirdly, ego motion is estimated using new stencils with removed moving objects. The next frame is developed by masking it with stencil without moving objects.

We separate non-stationary objects from the motion scene by checking the area of two consecutive silhouettes

$$A_t = \begin{cases} A_{NS}, & \text{if } A_t > A_{t+1} \\ A_S, A_{NS} & \text{otherwise} \end{cases}$$

where A_S is area of stationary object and A_{NS} is area of non stationary object This will simplify the selection process. To detect the relative distance and remaining non stationary objects (vehicles getting closer the host vehicle)we match silhouettes with respective templates as follows

1. Compare width-to-height ratios to identify the vehicle category (Car, Van, SUV, Bus etc.)
2. Obtain T_{min} (minimum template in the range) and T_{max} (maximum template in the range)from lookup table
3. Match with the silhouette iteratively by scaling to identify the vehicle
4. Verify it by symmetric property based vehicle identification For each contour we apply symmetric based analysis as proposed in [17] to separate vehicles from other objects. We identify vertical symmetry by overlaying two halves partitioned at scan line, in silhouettes of all detected images.
5. Use scaling factor to determine the distance

A. Confirming stationary objects and Determination of vertical shift of moving vehicles

We obtain image strips , based on the height of the object. Two image strips are matched with a shape matching method [16] calculated by aligning the two stencils obtained after the application of corresponding morphological operations.

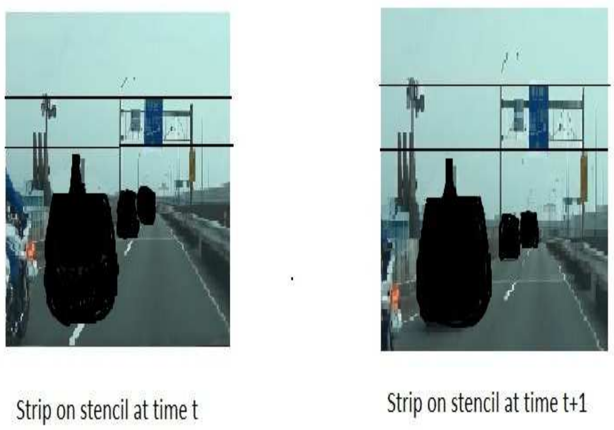

Fig. 4. Apply shape matching to two image strips to find their similarity

If two image strips are matched we conclude that the object is stationary otherwise it is non-stationary. To calculate ego motion we use vertical and horizontal strips on the stencil set ,and we use the theoretical basement proposed in [15].
Once the relative distance of moving vehicle is calculated using the scaling factor as stated above it can be further verified by calculating vertical shift of the bottom line of its bounding box in two consecutive(sampled) frames after the corresponding morphological operations.

B. Distance detection with night vision

Night time videos (or night vision videos) contain less information compared to daylight estimations. The only dominant data that we have to use for tracking is front and rear lights of the vehicles. Thus, the use of strip matching is no longer hold with this environmental setting. And it brings a new challenge as it is to deal with other lights fixed on the background, which causes false positive results. Another

Fig. 5. Vehicles detected after deselecting stationary objects

challenge is the high beams of oncoming vehicles which cover a bigger area and sometime are overlapping each other. We apply Dilation and Erosion morphological methods before the image are taken for further processing. We use another morphological operation where two sets of images are used one is the original image and another is the structuring element which have set of pixels in the predicted (two circular shapes overlapped each other)shape.

Fig. 6. Use of temples (circular) and Haar classifiers

We use two distinct methods to overcome this difficulty, one is to use the templates to check the availability of two cyclic white spots , the other is to use Haar classifiers to differentiate vehicle lights from the other lights in the background.

We reduce the search area by selecting the following procedure

1. Obtain the contour differences of stationary (fixed lights) and non stationary (moving lights)
2. Apply morphological operations (before frame matching)
3. Perform Haar classification to isolate front lights and rear lights
4. Use template matching technique if Haar classifier resolves

the front lights in step (3)

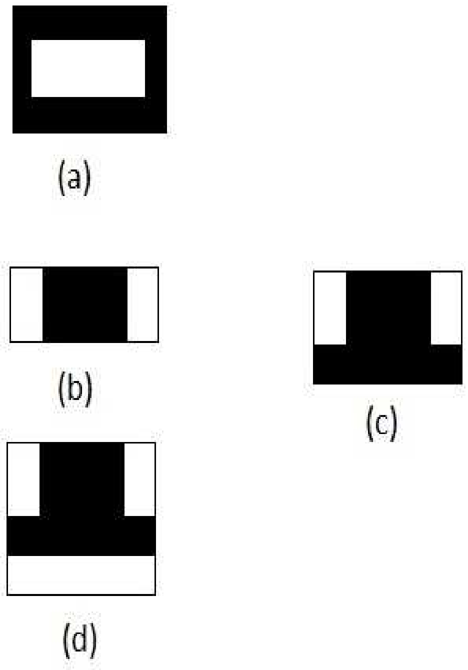

Fig. 7. Set of Haar classifiers

Here
Classifier (a) determines the presence of front lights
Classifier (b) determines the rear lights
Classifier (c) determines the rear lights and bottom dark part of vehicle
Classifier (d) determines the rear lights , bottom dark part and reflection of lights on the road

With the results from Haar classification, to distinguish rear lights from front lights lights, we apply a suitable threshold to identify red pixels in the image (see figure 8).

For all determined rear lights, vehicle's relative distance is calculated with width-to-distance lookup table values. Here the width is distance between two centers of white boxes of matched Haar classifiers.

We use a series of bi-circle templates to identify the front lights . This templates matching method itself estimates the relative distance of oncoming vehicles from host vehicle.

IV. Conclusion and Future work

This paper introduces a new method to track distance of oncoming and passing vehicles by applying contour detection and ego motion calculation by stencil matching algorithm. Contours are detected with temporal information received from a set of frames based on the changes in geometry of the contours. Once the ego motion is estimated in the scene with initial frames, it is recursively updated with the scene frames or stencils without disturbing objects. To verify the detection of hypothesised vehicle, it is further examined with symmetric feature analyses.

As a future work it is to extend the method to detect the motion of moving occlude vehicles and the identification of turning vehicles where the symmetric feature is no longer hold.

Fig. 8. Confirming rear lights by thresholding Red points

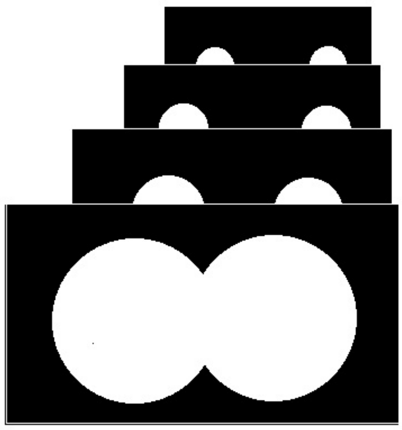

Fig. 9. Series of templates to isolate headlights

V. Acknowledgement

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