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NIGHT TIME TRACKING OF VEHICLES USING KERNELIZED CORRELATION FILTER AND CHANNELWISE RELIABILITY ESTIMATION

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ABSTRACT: Visual information is strongly deteriorated or at least degraded due to poor illumination conditions. This reduces the perceptive ability of vision systems significantly and can even lead to target loss, resulting in false estimation and/or false prediction of object behavior. In this an approach is implemented for the detection and tracking of moving object in an image sequence. Two consecutive frames from image sequence are partitioned into four quadrants and then the Correlation is applied to each sub frame. The sub frame which has minimum value of Correlation, indicates the presence of moving object. Next step is to identify the location of the moving object. Location of the moving object is obtained by performing component connected analysis and morphological processing. After that the centroid calculation is used to track the moving object. As our tracker has only little computational cost, it is appropriate for use cases with real-time requirements like in automotive or industrial applications.

KEY WORDS: Nighttime vehicle tracking, correlation filter, kernel zed expert, reliability estimation, weather robustness, Centroid, Tracking, Processing time, Detection Rate.

I.INTRODUCTION

A vision-based system for detecting the road environment for driver assistance and autonomous vehicle guidance is an emerging research area. Accordingly, many researchers have developed valuable techniques for recognizing interesting vehicles and obstacles from images of road Environment outside the car, to facilitate applications on the camera-assisted system that assists drivers in understanding possible hazards on the road, and automatically controlling the apparatus of vehicles, such as headlights, windshield wipers, etc. A vision-based vehicle and obstacle detection system is aiming at identification of vehicles, obstacles, traffic signs and other patterns on the road from grabbed image sequences by means of image processing and pattern recognition techniques. By adopting different concepts and definitions on interesting objects on the road, different techniques are applied on the grabbed image sequences to detect them as vehicles or obstacles. For locating vehicles in an image sequence, the task can be carried out by searching for specific patterns on the images based on typical features of vehicles, such as shape, symmetrization, or their surrounding bounding boxes. Until recently, most of these works focused on detecting vehicles under daytime road environments. However, under bad-illuminated conditions in nighttime road environments, those obvious features of vehicles which are effective for detecting vehicles in daytime become invalid in nighttime road environments.

Around evening time, just as under dim lit up condition as a rule, the main visual highlights of vehicles are their headlights and taillights. Notwithstanding, there are likewise numerous other illuminant sources existed together with the vehicle lights in evening time street situations, for example, road lights, traffic lights, and street reflector plates on ground. These non-vehicle illuminant sources cause numerous challenges for identifying genuine vehicles in evening time street scenes. In this examination, we propose a compelling evening time vehicle discovery technique for recognizing vehicles by finding and breaking down their headlights and taillights.

This implemented strategy involves the accompanying handling stages. Initial, a quick brilliant article division procedure dependent on programmed staggered histogram thresholding is performed to remove pixels of splendid items from the got evening time street scene pictures.

The benefit of this programmed staggered thresholding approach is its strength and flexibility for managing different lit up conditions around evening time. At that point these splendid segments are then gathered by a projection-based spatial grouping procedure to acquire potential blending headlights of approaching vehicles, and taillights of going before vehicles. In like manner, a lot of distinguishing proof principles are connected on each gathering of brilliant items to decide if it speaks to a genuine vehicle. At long last, the separation between every one of the distinguished vehicles and the camera-helped vehicle is evaluated and revealed.

As of late, traffic security, particularly out and about, has been progressively drawing open consideration, as street traffic damage is positioned as one of the top reasons for human losses [1]. All the while, propelled driver help frameworks and self-governing vehicle innovation are utilized to decrease car crashes. One key method of these frameworks is to identify and follow other traffic members so as to investigate and anticipate their practices. Hence, following approaches, particularly those dependent on vision strategies, become increasingly main stream.

Contrasted with other sensor arrangements, vision-based frameworks are relative modest, lightweight and adaptable. Additionally, they can give rich visual data that can be utilized to perceive various article classes. These properties have prompted an extensive improvement of following execution [2]. One agent of these techniques is the discriminative following methodology [4], which fuses AI procedures. Such sort of tracker prepares a classifier for each caught article dependent on the separated picture highlights. The classifier is connected on the following picture to look through the competitor with the most comparable appearance. This new up-and-comer is then used to refresh both the prepared model and the article states (e.g., area in the picture). As ground-breaking classifiers like the support vector machine (SVM) can be sent, high accuracy in following different item classes (counting vehicles) can be accomplished.

II. RELATED WORK

By exploiting training set with circulant structures and introducing the kernel tricks both tracking precision and runtime performance have been further improved. To enhance the classifier training, several strategies are proposed such as spatial regularizations, estimating spatial priors, learning support vectors, multi-memory stores and adaptive training set managements. As deep learning has become more and more popular among the computer vision community, it has also been incorporated in tracker models to obtain more powerful features yet at the cost of decreased computational efficiency. Due to these efforts, CF-based trackers currently achieve top performances for various object classes (including vehicles). However, most of these tracked objects are still observed with relative good illumination, e.g., in daylight. As visual features are weakened in badly illuminated cases, to track vehicles in the night, most of the research works prefer to locate the bright areas of a vehicle in the image.

Representatively, clustering processes on bright objects have been applied and to grab the head- and taillight patterns. Similar recognition approaches can be seen but are augmented by geometric and motion pairing. Aside from that, shapes of lights have been also incorporated to eliminate false objects caused by on-road reflections. In contrast, focuses on the recognition of

turn signals and utilizes the Nakagami distribution to build scattering models. Although vehicle lamps appear as quite distinguishable in the night, they may not cover the whole visible area of a vehicle. Other parts with clear contour or color are also worth being considered as appearance features in order to improve the tracking performance. However, such kind of deep digging on available visual information of a tracked target is rare to be seen in most research work.

Furthermore, some tracking approaches are based on specific hardware. For instance, a specifically configured camera is utilized in to control the exposure and color processing operations. In tracked objects are verified by an additional sonar sensor, yet with a limited range of measurement. Instead of that, thermal cameras are adopted to enhance the contrast of objects in the image. However, the performance of thermal sensors can also be interfered by unexpected heat sources such as bonfires

As visual object tracking has been an active area among the research community, drastic advances especially in feature selection and model building have been witnessed in the last decade. According to appearance models, trackers generally can be categorized into two groups: generative and discriminative approach. In the first category, the object appearance is modeled by generative features such as templates or sparse coding. For instance, extract color histograms from small image patches to represent pedestrians. Additionally, deploy point features to boost the performance in matching objects. In comparison, discriminative approaches reinterpret tracking as a classification problem by training a classifier just in time from previous observations to find the target in the following image. Such kind of a concept establishes the bridge to introduce numerous machine learning technologies into conventional tracking research.

In prior work, classification methods like boosting and random forests have been introduced to build discriminative trackers. As they are ensemble learning approaches, in spite of high tracking precision, the sampling in large data sets brings inevitable heavy computational burdens. Conversely, by integrating localization and classification in the same scheme, significant improvements on computational efficiency has been achieved by structured SVMs. Leveraging the strength of structured SVMs, the correlation filter (CF) has also become attractive in tracking research, as both of them share similar structures. The CF-based tracking approach has met tremendous progress in recent years. For precision improvement, correlation filters with multiple channels are designed to adopt more discriminative features such as histogram of oriented gradients (HOG) and color attributes.

III. EXISTED SYSTEM

For a better understanding of this work, we would like to give a short review of the kernelized correlation filter. In this method, the training samples for the classifier are extracted based on an image patch x of M × N pixels with the target located in its center. Instead of sliding windows, each sample xi is obtained by circularly shifting the image patch with $i \in \{0,\cdots, M-1\}\times\{0,\cdots, N-1\}$ pixels. Its label $y_i \in [0, 1]$ is calculated by a Gaussian function with respect to the Euclidean distance between the centers of image patch x and the shifted version. The solution can be obtained in a closed form as

$$\boldsymbol{\alpha} = \mathcal{F}^{-1}\left(\frac{\mathcal{F}(\mathbf{y})}{\mathcal{F}(\mathbf{k}^{\mathbf{xx}}) + \lambda}\right), \quad (1)$$

$$\mathbf{k}^{\mathbf{xx}'} = \exp\left(-\frac{1}{\sigma^2}\sum_{c}^{C} h(\mathbf{x}^c, \mathbf{x}'^c)\right) \quad (2)$$

The above equation shows Gaussian kernel with Standard deviation

The classifier is decomposed into a number E of kernel zed experts, each focusing on a few feature channels. The filter response of each expert is weighted by its corresponding coefficient vector and aggregated into the final response map, with its peak to indicate the location of the most similar candidate of the target. The term kx is calculated by accumulating the correlation of each feature channel, regarding them with equal contributions in measuring similarities between image samples x .

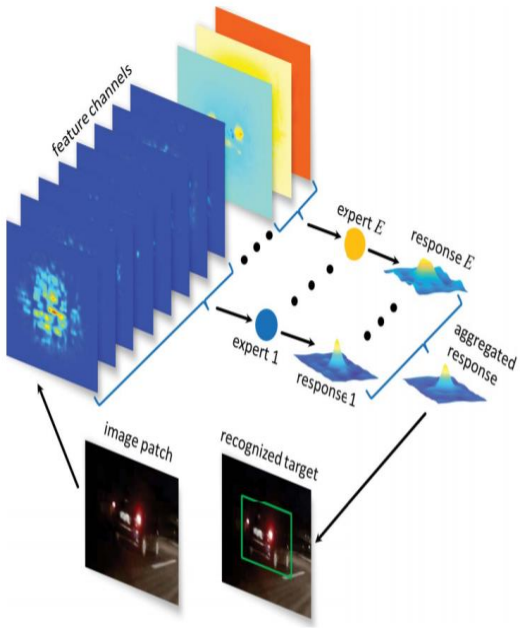

Fig. 1: Existed System

Although this assumption works well in tracking objects in scenarios of good lighting conditions, it can be troublesome to deal with objects in low illuminated cases, particularly in the night. As each feature channel may represent one type of visual features, they can suffer from different fading effects caused by low illumination. Thus, treating them equally can weaken the classification power of discriminative channels in the averaged filter response and make matching results vulnerable to noises from non-discriminative ones. Moreover, features from different channels may be extracted in various scales, a direct accumulation can also cause unbalanced weighting of different feature types. The idea is that we force each expert to focus only on a small number Ce of feature channels (Fig. 2), which are within the same type or scale, so that the corresponding kernel zed correlation kx can be restricted to these feature.

IV. IMPLEMENTED SYSTEM

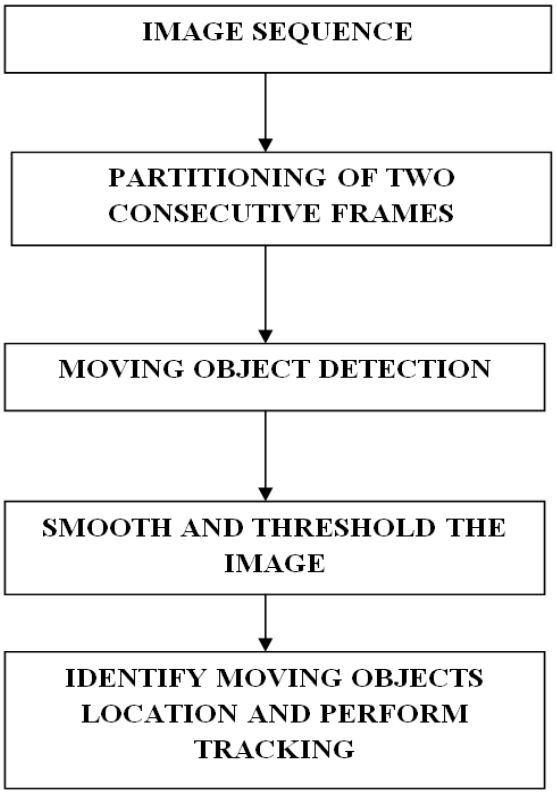

Fig. 2: Implemented System

Basic steps involved in the process are given in figure 2. As shown, input image sequence is taken from the static camera. Two consecutive frames from the image sequence are partitioned into four quadrants. Then moving object detection takes place after finding Normalized Cross Correlation between two partitioned frames. Moving Object detection in video involves verifying the presence of an object in image sequence and possibly locating it precisely for recognition. After detecting the moving object, the location of the moving object is obtained by performing component connected analysis. Tracking of the detected moving object takes place by calculating the centroids of the detected moving object. Tracking means the detection of a target over time, thus establishing its trajectory. The aim of object tracking is to establish a correspondence between objects or object parts in consecutive frames and to extract temporal information about objects such as trajectory, posture, speed and direction.

Basic algorithm steps for the detection and tracking of moving objects are given below. • Read two consecutive frames from the image sequence called as current frame and previous frame.
• Divide these frames into four quadrants.
• For ex: Current frame is divided into four parts called as x1, x2, x3 and x4. Similarly, previous frame is divided into four parts called as y1, y2, y3 and y4.
• Now find out the NCC of each sub image of current frame with the previous frame. After this there are four values of NCC, called as c1, c2, c3 and c4.
• Now find out the minimum value of NCC from these four values.
• To this minimum value of NCC apply the threshold.

• The threshold value is selected by taking average of four NCC values (i.e. c1, c2, c3 and c4).
• Suppose the minimum value of NCC is obtained at the first quadrant, it means that the moving object is present in that quadrant.
• Now operate in the first quadrant. Take the difference between the first quadrants of two consecutive frames. Then find the location of the moving object by performing component connected analysis and morphological processing.
• Centroid calculation is done for tracking the moving object.
• After this the second minimum value from the c1, c2, c3 and c4 is obtained. This is performed to check whether any other moving object is present in other part of the image.
• If the second minimum value is also greater than threshold then it means that the moving object is present in that quadrant. Now, identify the location of second moving object and track that object.
• Repeat the same procedure for the next frame.

V. EXPERIMENTAL RESULTS

Fig. 3: The tracking sequence car dark in night time and bad weather conditions

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Fig4. Tracking of a blur car

VI. CONCLUSION

A new method is introduced to track the vehicles at night time. By using kernel zed correlation filter effective output is not obtained. Hence a new correlation filter is introduced to detect and track the vehicle during night time. In implementing method a method called normalized cross correlation is used. Important advantage of this algorithm is that it requires very less preprocessing of the frames from image sequence (median filtering and contrast stretching). The algorithm is robust against changes in illumination and lighting conditions. In poor lighting conditions also the algorithm is giving better results.

VII. REFERENCES

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