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Vehicle Detection and Classification from Satellite Images Based On Gaussian Mixture Model

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Abstract— A dynamic vehicles are identified using background elimination techniques. The background removal method uses in the concept of GMM. This approach is tracking distinct feature, such as corner, edge line. The advantage of this approach is to tolerate partial occlusion, and not sensitive to image quality relative to other tracking methods, The SIFT features used here to an vehicle detection. This is done by using the images captured from the satellite. Each image is processed separately and the number of cars has been counted This method starts with a screening of asphalted zones to restrict the areas to detect cars and thus reduce false alarms. Then it will perform a feature extraction process given by the scalar invariant feature transform in which a set of key points is identified in the obtained image and opportunely defined. Successively, using a support vector machine classifier it discriminates between key points assigned to cars and all the others. The final step of the method is focused on grouping the key points belonging to the same car to get a "one key point–one car" relationship. Finally, the number of key points finally identified gives the amount of cars present in the scene.

keywords— Car detection, Feature extraction, Gaussian Mixture Model(GMM), Support Vector Machine(SVM), Scale Invariant Feature Transform (SIFT) ,Histrogram Of Gradient,Car Keypoint Merging.

I.INTRODUCTION

A new detection approach of automatic car counting method using satellite vechile images consists of two phases training phase and detection phase. In the training phase, image extract several features which includes local edge corner features and image colors. And to subtract the background using GAUSSIAN MIXTURE MODELS (GMM)[7]. It is the mixture of the Gaussian model distribution of background pixels that will be the scene to establish the statistical model for each pixel, and periodically update the background. This method uses background subtraction which ameliorates the adaptive background cumulation model and makes the system learn more expeditious and more accurately, as well as habituate efficaciously to transmuting environments. The objective of this research is to monitor the activies at traffic intersection for detecting the congestions, and then soothsay the traffic flow. **1**It has widely been realized that increases of preliminary transportation infrastructure and widened road, have not been able to relieve city congestion. As a result, many investigators have paid their attentions on Intelligent Transportation System (ITS), such as predict the traffic flow on the basis of monitoring the activities at traffic intersections for detecting congestions[2]. To better understand traffic flow, an increasing reliance on traffic surveillance is in a need for better vehicle detection such at a wide-area.

After background removal detection phase feature extraction has SIFT feature to detect the cars by using keypoint classification to eliminate more points from the list of keypoints by finding those that have low contrast or are poorly localised on an edge[2]. From a set of reference image SIFT keypoints of objects are first extracted and stored in a database By comparing individually each feature from the new image with this database, an object is recognized into a new image and using the Euclidean distance of the feature vectors the candidate matching features is found[15]. Subsets of keypoints that satisfies the object and its location, orientation and scale in the new image are identified from the full set of matches to filter out good matches[3].

Afterwards, using SVM the extracted features are used in order to classify pixels as nonvehicle pixel or vehicle pixel[5],[8]. It will not perform region based classification, which highly depends on results of the color segmentation algorithms such as mean shift. It is not neccessary to generate the multi-scale sliding windows either. The distinguishing features of the defined framework is that the detection task is given based on the pixel wise classification. Finally above all method are over and the result of counted cars in the satellite image is obtained.

In this paper, the screening step of asphalted zones to restrict the areas where detecting cars and thus to reduce the probability of false alarms. Then it will performs a feature extraction process given by the scalar invariant feature transform(SIFT) to which a set of consistent keypoints is identified. The algorithm then aims at the classification of these keypoints by discriminating between the points which belong to cars and all the others by a support vector machine (SVM) classifier[14]. The final step of procedure is focused on the grouping the keypoints belonging to the same car to get a "one key point–one car" relationship[1],[5]. At the end of the procedure, the number of key points finally identified gives the amount of cars present in the scene.

The main differences between our method and those available in the literature are as follows:

1) the car detection and description mechanisms;
2) our method is invariant to the car orientations;
3) it associates several pointers with the same car making the detection process more robust but requires a merging operation;
4) it allows handling occlusion problems due to shadows or trees for instance;
5) it combines the detection process with a screening operation of the asphalted areas;
6) it does not require a dictionary of precise car models.

II.IMPLEMENTATION OF PROPOSED SYSTEM

A.Screening

To make the detection faster and to reduce the number of false alarms, we restrict the investigated area by analyzing only regions where cars usually can be found. Assuming that cars are present only over areas covered by asphalt implies that a screening of these regions is needed.

B.Background Removal

In surveillance applications the first step is background removal . It reduces the computation required by the downstream stages of the surveillance pipeline. Background subtraction is reduces the space to be searched in the video frame for object detection by filtering and remove the uninteresting background from the video. Here Gaussian Mixture Model (GMM) algorithm for background elimination[1].

C.Gaussian Mixture Model (GMM)

The traditional Gaussian mixture model uses a mixture of the Gaussian model distribution of background pixels that will be the scene to establish the statistical model for each pixel, and periodically update the background[7]. The Gaussian model based on the screen to pure only when the background images with each pixel to calculate the mean and standard deviation, and the future prospects of the background information as a basis for classification.Another method is to calculate the probability of classification through the foreground and background pixels using the Bayesian classifier,or with the probability of hidden Markov model to achieve the classification of foreground and background.

The Gaussian mixture model is a single extension of the Gaussian probability density function. As the GMM can approximate any smooth shape of the density distribution, sooften used in image processing in recent years for good results.Assuming the Gaussian mixture model consists of and the combination of Gaussian probability density function, the Gaussian probability density function of each has its own mean,standard deviation, and weight, the weights can be interpreted by the corresponding Gaussian model of the frequency, theymore often appear in the Gaussian model the higher the weight[4].The higher frequency of occurrence, then find the maximumweight on the Gaussian probability density function, Finally,the Gaussian probability density function of the means pixel value is background image.

III.FEATURE EXTRACTION

Fig 1 represent the process and step of feature extraction. In this stage the local features detect the image frames. In this feature extration perform edge detection, corner detection, color transformation and classification. It perform a feature extraction process based on scale invariant feature transform (SIFT).

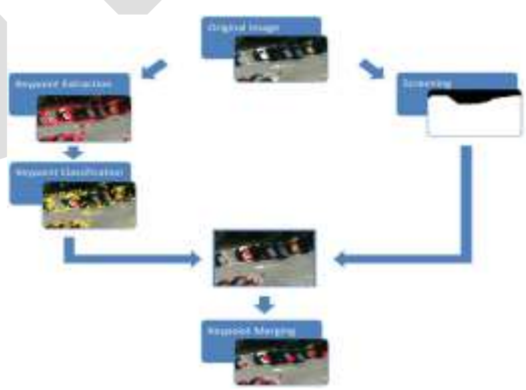

Fig 1 Diagram for feature extraction

IV.SCALE INVARIANT FEATURE TRANSFROM (SIFT)

From a set of reference image SIFT keypoints of objects are first extracted and stored in a database By comparing individually each feature from the new image with this database, an object is recognized into a new image and using the Euclidean distance of the feature vectors the candidate matching features is found. Fig 2 describes keypoints assing to the cars. Subsets of keypoints that satisfies the object and its location, orientation and scale in the new image are identified from the full set of matches to filter out good matches.

Fig 2 shows keypoint assing to the cars

The resoluteness of consistent clusters is performed rapidly by utilizing an efficient hash table and implementation in the generalized Hough transform. Each clusters of 3 or more features that accede on an object and then subject to further detailed model of verification and subsequently discarded the outliers. Determinately that a particular set of probability features designates the presence of an objects is computed, given the precision of fit and number of probable erroneous matches. Object matches and pass all the tests can be identified as veridical with high confidence.The algorithm firstly constructs a Transformation coefficients reduced matrix, and then smooths the DC Coefficients to generate the Tranformation Domain coefficients reduced images.Based on which SIFT feature is extracted. The experimental results show that with low loss of accuracy. SIFT feature extraction algorithm can significantly improve the computational efficiency of feature extraction, and will have great practical value in thecondition of high real-time requirements.SIFT algorithm, increases the computational time significantly.The image doubling is eschewed but the search for extrema is performed over the whole image including first and the last scale. If any image is doubling that case the pixel comparing the image and carried out only with available neighbors.

V.DIFFERENT FUNCTION OF KEYPOINTS

A.Keypoint Localization

This stage attempts to eliminate more points from the list of keypoints by finding those that have low contrast or are poorly localised on an edge. This is achieved by calculating the Laplacian. This removes extrema with low contrast. To eliminate extrema based on poor localisation it is noted that in these cases there is a large principle curvature across the edge but a small curvature in the perpendicular direction in the difference of Gaussian function. If this difference is below the ratio of largest to smallest eigenvector, from the 2x2 Hessian matrix at the location and scale of the keypoint, the keypoint is rejected.

B.Keypoint Descriptor

Antecedent steps founded the keypoint locations at the particular scale and assigned orientation to them. This ascertained invariance to image location, scale and rotation. This is need to evaluate a descriptor vector for the each keypoint such that the descriptor is partially invariant and highly distinctive to the remaining variations such as 3D viewpoint, illumination, etc. This step that is performed on the image is most proximate in scale to the keypoint's scale.[10] A set of orientation histograms is first engendered on the 4x4 pixel neighborhoods with 8 bins each. This histograms are then computed from the magnitude and orientation values of the samples in a 16 x 16 region around the keypoints such that each histogram contain samples from a 4 x 4 subregion of the pristine neighborhood region. The magnitudes are further then weighted by a Gaussian function with equipollent to one moiety the width of the descriptor window. This descriptor then becomes a vector of all values of these histograms. The vector has 128 elements since there are 4 x 4 = 16 histograms with 8 bins each. These vector is then normalized to unit length to enhance invariance to affine transmutations in illumination[1] . A threshold of 0.2 is then applied and the vector is once again normalized in order to reduce the effects of non-linear illuminations. Albeit, the dimension of the descriptor seems to be high, then descriptors with lower dimension than this do not perform as such across the range of matching tasks. So the computational cost still remains low due to the approximate method utilized for finding the most proximate-neighbor. Longer descriptors perpetuate to do more better but not that by much and there is a supplemental peril of incremented sensitivity to distortion and occlusion. It is shown that feature matching precision is above 50% for the viewpoint changes of up to 50 degrees. Therefore minor affine changes are invariant by SIFT descriptors[6] . Matching precision is withal quantified against number of keypoints varying in the testing database to test the distinctiveness of SIFT descriptors and it is shown that matching precision decreases only very remotely for prodigiously and sizably voluminous database sizes, thus betokening that SIFT features are highly distinctive.

C.Orientation Assignment

The SIFT-feature location is resolute, A main orientation is assigned to each feature predicated on local image gradients. For each pixels of the region around the feature locations the orientation and gradient magnitude are computed respectively. From the SIFT feature description,it is evident that SIFT-feature algorithm can be understood as a local image operators which takes the transforms and an input image it into an accumulation of local features.To utilize the SIFT operator for object apperception purposes, it is applied on two object images, a model and a test image, its for the case of a victuals package[3],[10]. As shown, the model object image is an image of the object alone taken in predefined conditions, while the test image is an image of the object together with its environment. To find corresponding features between the two images, which will lead to remonstrate apperception, different feature matching approaches can be utilized. According to the Most proximate Neighborhood procedure for eachfeature in the model image feature set the corresponding feature must be probed for in the test image feature set.The corresponding features is one with the most diminutive Euclidean distance to the feature. A dyad of corresponding features is called a match. To determine whether the match is positive or negative, a threshold can be utilized.

D.Keypoint Classification

Once the set of keypoints, with their respective descriptors is extracted, the goal of the next stage of the process is the discrimination between keypoints which belong to cars and keypoints which represent all other objects (“background”). Since the dimension of the extracted features is relatively large, it is recommended to adopt a suitable classification method such as the SVM classifier. Before applying a classification based on an SVM classifier, further information will add. In fig 3 the Structure of the SIFT descriptor to the keypoint descriptor in order to potentially improve its discrimination power.

Fig 3 Image of keypoint classification

The first six features will add are related to color information. Indeed,the think that the addition of some proprieties strongly associated with the object itself can lead to a better discrimination.

Table 1 keypoint classification accuracy in percent

Features	Car	Background	Total
SIFT	27.72	98.49	98.15
SIFT + Color	50.07	98.61	98.37
SIFT + Morphology	52.75	98.67	98.40
SIFT + Color + Morphology	48.81	98.7	98.34

The table1 describe the SIFT description vector, obtained at the end of the feature extraction procedure, takes origin from the results achieved with extra color and morphological features. Indeed, the addition of 24 features (i.e., RGB, HSV, and 3 × 6 morphological features) allows us to improve the results of the keypoint classifications.Even if car colors can be very heterogeneous, in numerous cases, their colors appear dissimilar to the appearance of dominant objects in the contextual environment (e.g., asphalt, houses, and green areas) [9]. For this reason, the think that the use of features linked to colors spaces can help in the discrimination.

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VI.CAR KEYPOINT MERGING

At the end of the keypoint classification procedure, the number of keypoints associated with the car class can be larger than the number of cars itself. The reason is that it is likely that a single car is marked by more than one keypoint. Let Kc = {k1, k2, . . . , kN } be the set of N keypoints found for the car class in the considered image I (x, y); the goal is to estimate the number of cars present in I (x, y) and to identify them in a univocal manner. To pursue this scope, it will develop an algorithm to group the keypoints which belong to the same car. Since the merging is performed in the spatial image domain, it will rely on a merging criterion based on a spatial distance between the keypoints in order to identify neighboring keypoints and possibly merge them into a unique keypoint representing the car on which they lie.This method is shows in fig 4.

Fig 4 Car Keypoint Merging

The main steps of our merging algorithm are summarized.
Step 1: The spatial coordinates of the keypoints contained in the set *Kc* are used as input of the algorithm.
Step 2: To the vector of parameters, a further parameter *m* is added and initialized to 1. It will act as a counter to keep trace of the number of "merging operations" done with that keypoint.
Step 3: A matrix $N \times N$ containing the Euclidean distances in the spatial domain between all keypoints is computed.
Step 4: The two keypoints (k_i , k_j) with the smallest distance d_{min} are selected.
Step 5: If $d_{min} < T_m$ (threshold) $\rightarrow k_i$ and k_j are merged into a new point k_t which will replace the two keypoints in the set *Kc*.
Step 6: The matrix containing the distances is then recomputed with the new point.
Steps 3–6 are repeated until $d_{min} > T_m$.
Step 7: Assuming that the points with a value of *m* smaller than 2 are isolated points only the points with $m > 1$ are kept. The number of resulting merged keypoints represents finally the estimation of the cars present in the image. This step is useful to detect.

VII.RESULTS AND DISCUSSION

A.Using MATLAB Software to detect the result.
Satellite Image

Below image is taken from the satellite for couting the cars using SVM classification.

Fig 5 Input Image Taken From Satellite

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B.Image Frame Using Histogram Of Gradiant

To convert the original image to image frame using histogram of gradiant to frame the image by using cell size, block size and block overlapping methods.

Fig 6 Output Of Histrogram Of Gradiant

C.Background Removal Using GMM

To subtract the background removal by using gaussian mixture model to subtract the poor pixel from the image.

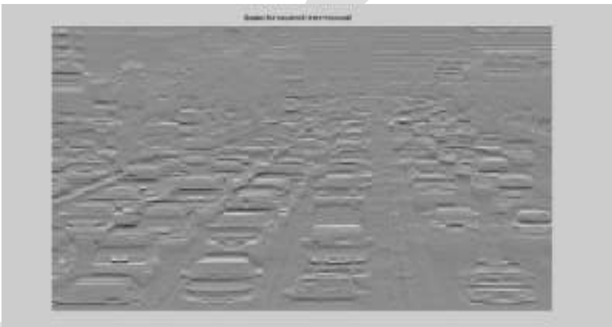

Fig 7 Output Of Backgournd Removal

D.Noise Reduction

The image contains lot of noise in the pixel using lowpass filter reduce the noise in noise reduction method.

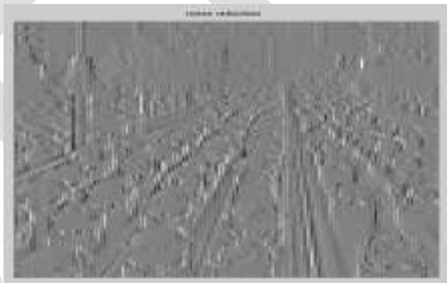

Fig 8 Output Of Noise Reduction

E.Edge Detection

Using edge detection method the edges of the cars are identified in the below image.

Fig 9 Output Of Edge Detection

F.Feature Extraction Using SIFT

In feature extraction the SIFT transform used to assign the keypoint for the cars and detect the keypoint classification and keypoint descriptor.

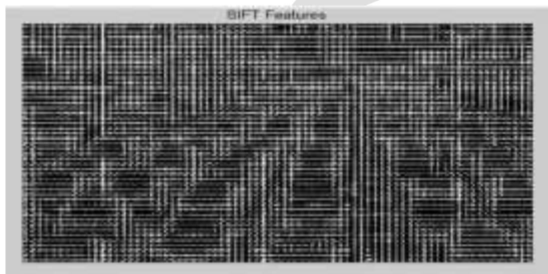

Fig 10 Output of Feature Extraction

G.Car Counting Using SVM Classification

By using SVM classification to access the hyperplane of the image and counting the cars in the given image.

Fig 11 Output Of Automatic Car Counting Method Using Satellite Vehicle Image

VIII.CONCLUSION

The automatic car counting detection have four-stage of procedure to develop the satellite images.The procedure start with a background removal using GMM to detect the regions covered by asphalt assuming that usually cars in an asphalted regions. This procedure permits us to reduce the false alarms. The second stage is feature extraction in this SIFT is used to assing keypoints to images using HOG.The third stage is SVM classification to merge all the keypoints in an image. This step is necessary because, at the end of the keypoint classification, a car is typically identified by more than one keypoint. Final stage is counting the cars in satellite images.Furthermore,Detecting all vechile using morphological filter and reduce the noises in the satellite images

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