ROADGUARD
Highway Control and Management System

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Abstract: In this paper, we propose a new approach, called Road*Guard*, for Highway Control and Management System. RoadGuard is based on counting and tracking moving vehicles robustly. Our system copes with some challenges related to such application processing steps like shadow, ghost and occlusion. A new algorithm is proposed to detect and remove cast shadow. The occlusion and ghost problems are resolved by the adopted tracking technique. A comparative study by quantitative evaluations shows that the proposed approach can detect vehicles robustly and accurately from highway videos recorded by a static camera which include several constraints. In fact, our system has the ability to control highway by detecting strange events that can happen like sudden stopped vehicles in roads, parked vehicles in emergency zones or even illegal conduct such going out from the road. Moreover, RoadGuard is capable to manage highways by saving information about date and time of overloaded roads.

1 INTRODUCTION

Highway surveillance is an active research subject in computer vision. In fact, the rapidly increasing of car's numbers makes the roads overloaded and traffic congestion growing up. The traditional solution has been to construct more and larger roadways, but that is no longer seen as an option by transportation planners, due to the high financial, social, and environmental costs of such giant projects. More efficient use of the existing roadways especially highways network using advanced technologies seems to be the answer. Therefore, in perfect harmony with the big international orientations, considerable investigations aim to keep the world moving safely, comfortably, economically, and without harm to our environment by creating the best transportation system through proactive excellence, leadership and innovation in services. The objective is to ensure that roadways continue to be safer and more technologically up-to-date. Software solutions like Highway Control and Management systems (HCMSs) are used to solve these problems. These systems can lead to semantic results, such as '87 cars are in the right side of the highway' or 'an obstacle is on the road!!' or 'car No.5 is faster than car No.1' etc.

Semantic results of HCMS are based on counting and tracking moving vehicles starting by detecting moving objects (foregrounds). In fact, foregrounds detection could be considered as one of the fundamental and critical step in this field. Moving object detection methods cannot differentiate real foregrounds from their shadow since they shared some motional features. This has bad effects on performance of the upper steps of HCMS. Actually, researches related to these tasks are still far from being solved.

In this paper, we present *RoadGuard*, a new HCMS that counts and tracks robustly vehicles in highway. Moreover, our system copes with different challenges such as shadow, occlusion, ghost and others outdoor conditions. Since shadow detection and removal takes a careful consideration in HCMS, we propose a new algorithm which detect moving shadows and suppress the cast part. Indeed, we adopt a tracking technique that resolve occlusion and ghost problems.

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This paper is organized as follow. In section 2, we started out with over viewing state of art on common process steps of HCMSs. Following that, our proposed approach *RoadGuard* is reviewed in section 3. In section 4, an intensive experimental evaluation and comparison results are discussed. The proposed approach is summarized and future works directions are presented in section 5.

2 LITERATURE SURVEY

In this section, we give a state of art on the common process steps of HCMSs. In general, process of such systems includes four steps: (1) Moving object detection, (2) Shadow detection and removal, (3) Tracking and (4) Counting. The (1), (2) and (3) are widely treated in literature. The proposed approaches for each step are presented in the following subsections.

2.1 Moving Object Detection

Moving object detection is a well known research area in computer vision. Many methods have already been proposed in this field. We classify contributions reported in literature into four main categories according to the inter-image processing they adopt: detection based on Inter-Frame Difference (IFD), detection based on Background Modeling (BM), detection based on Optical Flow (OF), and detection based on Hybrid approaches.

BM methods (Tang, 2007) (Grimson, 1998) (Elhabian, 2008) are the most popular approach, they detects moving objects by comparing background model to each input frame. The efficiency of the BM methods depends on the ‘ideal background model’ that is not easy to obtain and easy to be influenced by the environmental conditions.

2.2 Shadow Detection and Removal

Shadow is occurred when a direct light from a light source is blocked by a moving object. In fact, there are two types of moving shadow: cast and self shadow (Cucchiara, 2001). Generally, the self shadow appears in the portion of a moving object which is not illuminated by direct light. Indeed, the cast shadow presents the area projected by the moving object in the direction of direct light.

The moving shadows detected erroneously as part of foregrounds affect the shape of the real moving objects and/or can cause occlusion between them. Thus, moving shadow presents the most serious problem in the performance of the upper levels of computer vision applications such as HCMS. The core problem discussed in literature is the detection and suppression of cast shadow and not self shadow since it is a part of the moving object. Indeed, we classify previous works into two categories of approaches, according to the decision process, which are: Statistical (Julio, 2005) (Mikic, 2000) and Determinist (Cucchiara, 2001) (Xiao, 2007). In the statistical approach, probabilistic functions are used to describe the class membership. In the determinist approach, an on/off decision is used to classify each pixel to shadow/non-shadow pixel. Moreover, two subclasses are presented, the Determinist Model Based (DM) and Determinist Non-model Based (DNM). DM methods require a priori knowledge about shape and motion of objects such as vehicles or human bodies (Kilge, 1992). Despite its simplicity, this method cannot be robust to many variations like illumination, objects shape, shadow edge. Besides, DNM methods classify pixels to shadow/non-shadow pixels without any prior knowledge about the scene (Cucchiara, 2001).

2.3 Tracking

Object tracking is used to estimate the trajectory of moving objects over time in every frame. However, the complexity of tracking objects is more complicated by abrupt object motion, occlusion between moving objects and/or between background and foreground objects. Several tracking methods (Kass, 1988) (Masoud, 2001) (Kanhere, 2006) are proposed in literature. We distinguish three major tracking approaches which are: Region-based, Boundary-based and Feature-based approaches. The Region-based methods rely on information provided by the entire region such as texture, size, color, shape and motion based proprieties using motion estimation techniques. These methods work well for small numbers of moving objects. However, they cannot solve the occlusion problems in dense traffic. The Boundary-based methods rely on information provided by the moving objects edges. A good initialization step is required. We notice that Boundary-based methods do not work well in presence of occlusions because the model is strongly dependent on local-based information that can be inaccurate. The Feature-based methods perform with tracking the moving object’s sub-features such as distinguishable points, lines or corners which are extracted from the blobs between frames. Tracking methods based on features are useful in situations of partial occlusions where only a portion of a moving object is visible.

3 PROPOSED APPROACH

RoadGuard is based on a set of steps: (1) Moving region detection to generate foreground mask, (2) Cast shadow detection to obtain cast shadow pixels mask, (3) Real moving object detection, (4) Tracking and counting real moving objects.

Each *RoadGuard*'s step is detailed in next sections.

3.1 Moving Region Detection

Accurate segmented moving regions are obtained by generating moving pixels mask and grouping the connected foreground pixels.

To detect moving pixels, we have adopted BM approach. BM methods can be recursive or non-recursive. The non-recursive methods use a sliding window to estimate the background. They build a buffer of frames and estimate the background model with temporal variation of each pixels value in the buffer. Besides, the recursive methods update periodically a simple or multiple background models for each input frame. Since recursive background models require less storage, we use the recursive version of Approximate Median (AM) method (McFarlane, 1995) to detect moving pixels. This method is able to deal with illumination and scene changes.

The AM method presents an accurate technique for background model updating. It updates periodically a background model for each input frame.

This process starts by initializing a reference with the first input frame. Then, if a pixel in the current frame has a value larger than the corresponding background pixel, the background pixel is incremented by 1. Likewise, if the current pixel is less than the background pixel, this latter is decremented by 1. In this way, the background eventually converges to an estimate value where half of the input pixels are greater than the background and the other half is less than the background, approximately the median.

Moreover, each pixel is classified as belonging to the foreground (assigned 1) or background (assigned 0) after the updating process. A binary moving pixels mask (M) is generated by a comparative stage between the input frame (I) and the background model (B). This comparative stage is based on a pre-determined threshold (Th) (for highway sequences equals to 25).

The obtained foreground pixel masks contain lot of misclassifications which correspond to cast shadow pixels detected erroneously as foreground pixels. This misclassification causes occlusion between the moving objects

Thus, we present our contribution in detecting cast shadow in the next section.

3.2 Cast Shadow Detection

In our approach, we identify cast shadow pixels without using the foreground masks. The basic idea is to detect all moving shadows in a frame sequence and then substitute from it the self shadow. Furthermore, we start by classifying each moving pixel into shadow/non-shadow. Then, we suppress the self shadow part from the moving shadow mask.

3.2.1 Automatic Classification of Moving Pixels

We consider shadow as moving pixels that have lower intensity value. For that, we adopt three successive differences to detect it. In fact, we consider four successive grayscale frames (f), (f-1), (f-2) and (f-3). Firstly, we perform by differences between ((f),(f-1)), ((f),(f-2)) and ((f), (f-3)) to obtain grayscale images I_1, I_2 and I_3 respectively. Secondly, we compute for I_1, I_2 and I_3 the respective binary masks MI_1, MI_2 and MI_3.

Furthermore, we propose an iterative algorithm to each difference (I_i). In our algorithm, we define two classes: (S) for shadow and (NS) for non-shadow and two variables last and current which represent respectively the value of the threshold in last and current rounds.

We proceed by classifying pixels according to their intensity value. Then, the current value is updated by taking the median value between the medians of the two classes S and NS.

We iterate these instructions until the current value is equal to last value. We notice that the loop iteration converges rapidly after three or four iterations. Besides, the moving shadow mask (MI_i) is obtained by applying a logical AND between the three masks: MI_1, MI_2 and MI_3. Indeed, pixels of class S are assigned 1 in MI, 0 otherwise.

3.2.2 Self Shadow Detection

Considering the similarity between visual features of self and cast shadow pixels, this phase constitutes a considerable work. We propose to build an automatic self shadow detection solution based on a machine learning approach using a set of manually classified shadow pixels from highway frames, in order to generate a predict model, which makes it possible to classify shadow pixels into two classes: self shadow and non-self shadow. We are based on KDD process (Fayyad, 1996) to extract useful knowledge from volumes data. The general principle of the classification approach is the following:

$$C : S \rightarrow \varsigma = \{\text{self shadow}, \text{non} - \text{self shadow}\}$$
$$P \in S \rightarrow C(P) \in \varsigma$$

Let S be the population of shadow pixels to be classified. To each pixel P of S one can associate a particular attribute namely; its class label C. C takes its values in the class of labels (0 for self shadow, 1 non-self shadow).

To do it, firstly, we split our corpus into training data set and test data set and we identify the effectiveness shadow pixels features in order to build a two dimensional table from our training corpus. Each table row represents a shadow pixel and each column represents a feature. In the last column, we save the shadow pixel class (0 or 1). Brightness, color and edge distortions are the most exploitable features for describing shadow pixels in literature. Secondly, we employ supervised learning to produce a significant predict model. In literature, there are several techniques of supervised learning, each having its advantages and drawbacks. So, among the most criterion to compare supervised learning techniques is the comprehensibility of the learned model wish leads us to a well-accepted techniques, that is, the induction of decision trees (Hammami, 2006). The SIPINA technique (Zighed, 1996) was used in our work to predict model.

Considering this model, self shadow pixels (assigned 1 in MI) are restored in the foreground pixels mask (M).

3.3 Real Moving Object Detection

After the post-processing step on the masks of foreground (M) and cast shadow (MI), a simple difference between them leads to get the real moving objects mask (RMO) without their shadows.

3.4 Tracking and Counting

The control phase of our system is based on tracking vehicles in a defined region of interest (ROI) and the emergency area.

We adopt a mean shift tracker based on features selection method (Nedovic, 2008). Several images features are computed for the Real Moving Objects (RMO). These features are classified into two main classes: color based features and texture based features. The color based features support the RGB, HSV and normalized RGB color spaces. The RGB color space reflects any changes in lighting intensity and color in the ROM. Normalized RGB (rgb) is considered as invariant feature to the lighting intensity changes. The HSV color space is based on human color perception. The texture features include co-occurrence matrixes, Gabor filters and Wavelet packets. Co-occurrence matrixes can distinguish between region pixels with the same color distribution and different texture. Both Gabor filters and Wavelet packets identify a texture changes since the energy signatures of different textures will be different.

In the mean-shift tracker, the real moving objects are characterized by the probability density functions (pdfs) of their color or texture features. Unlike the most tracking methods wish use fixed features as an indicator of the RMO location, the adopted tracker use an adaptive feature selection. In fact, the selection issue is seen as a RMO class discrimination problem. Distribution of the two classes is estimated by computing their features histograms. Discriminative power of the features evaluated independently is based on the variance ratio measure of likelihood distributions.

We obtain a positive value for RMO features and a negative one to those corresponding to the background. The distribution values in the likelihood images are used as an input to the Augmented Variance Ratio (AVR). We sort features according to their AVR score and top N features are used for tracking the object.

The management phase of the *RoadGuard* is based on counting vehicles in highways in order to obtain statistics information. In fact, we have implemented an algorithm which counts moving vehicles based on the enhanced provided masks and save some important information like the date and time of overloaded highways. Counting process is done in the ROI. The counter is incremented for each vehicle enters the ROI. Also, we have defined a number of vehicles (here more than 2) to generate an alert and save an overloaded event.

4 EXPERIMENTAL RESULTS

In order to validate our system, *RoadGuard* was evaluated by intensive experiments. We carried out our study on a set of highway sequences very referred in researches which are: $Highway_i$ {i=I,…,V}[1]. These sequences are recorded in typical conditions that include shadows. This section presents some results of these experiments.

Since pixels classifications into foreground or shadow pixels has important effects on performance of the upper steps of *RoadGuard,* the evaluation can be assessed by segmenting manually pixels of significant frames[1] to compute three global indicators: (1) Global Error Rate (GER), (2) A Priori Error Rate (PER) and (3) A Posteriori Error Rate (PSER). GER is the complement of classification accuracy rate, while PER (respectively, PSER) is the complement of the classical recall rate (respectively, precision rate). We identify two classes A and B which represent respectively "moving pixel" and "non-moving pixel".

To illustrate the relevance of our system, we present the obtained results for the set of significant frames[1]. Figure 1 and Figure 2 show respectively GER and PER(A)-PSER(A) before and after suppressing cast shadow.

The aim of cast shadow detection and removal is to decrease GER and PSER (A). The average value of the obtained GER in our experiment is decreased from 12% (88% correct classification) to 5,78% (94,22% correct classification) after suppressing cast shadow. Figure 2(a) shows that PSER (A) is almost the time greater than the PER (A), this means that the algorithm classify pixels erroneously as moving ones. These pixels correspond to the cast shadow pixels. The low PER (A) (average value equal to 17.45%) shows the robustness of the whole system against the environmental changes. After removing the cast shadow, the average value of PSER(A) is decreased from 49.78% to 23.74% which means that our *RoadGuard* performs highly in detecting cast shadow. Thus, a better segmentation of moving vehicles is provided. These results confirm the important affect of shadow problem.

The high-quality results given above allow us to compare our contribution with other existing techniques. The obtained results are compared to the best results of each shadow detection approach represented by well-know methods (Table1) given in a comparative reviewing (Prat, 2003).

Let ε represents the complement of the global error rate (GER) and η represents complement of the a priori error rate (PER) of the shadow pixels class. The results show the robustness of our proposed algorithm against shadow challenge.

The tracker of the *RoadGuard* is able to draw the trajectory of a moving object (Figure 3) in spite of its speed (fast/slow), shape (big/small) or location (near/far from the camera).

Table 1: Comparative Results.

	ε %	η %
SNP	81.59	63.76
SP	59.59	84.70
DNM1	69.72	76.93
DNM2	75.49	62.38
Our results	93.51	82.55

Moreover, *RoadGuard* is able to count vehicles (Figure 3) and save some important information like the date and time of overloaded highways.

5 CONCLUSIONS

In this paper, a novel and accurate approach *RoadGuard* for Highway Control and Management System is presented. The system is enough capable to detect, count and track vehicles in highway while no scene-specific knowledge is required. *RoadGuard* was evaluated with various video files against different Highway conditions. According to the presented results, we can conclude that we can consider *RoadGuard* as a robust computer vision application. In fact, our approach combines rapidity of adaptation in scene changes, a high precision in moving object detection, performance to detect and suppress cast shadow and accuracy to count and track moving vehicles.

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[1]The Highway video sequences are courtesy of the Computer Vision and Robotics Research Laboratory at UCSD.

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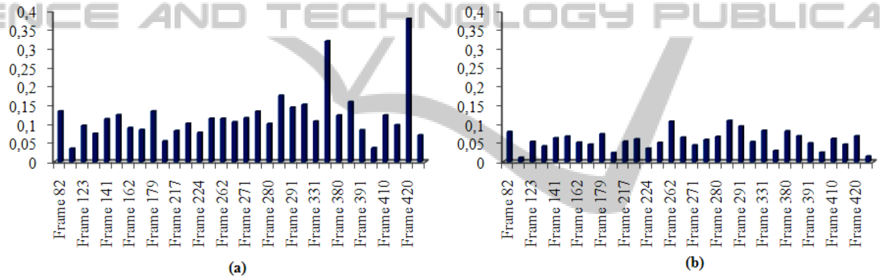

Figure 1: GER (a) before and (b) after suppressing the cast shadow.

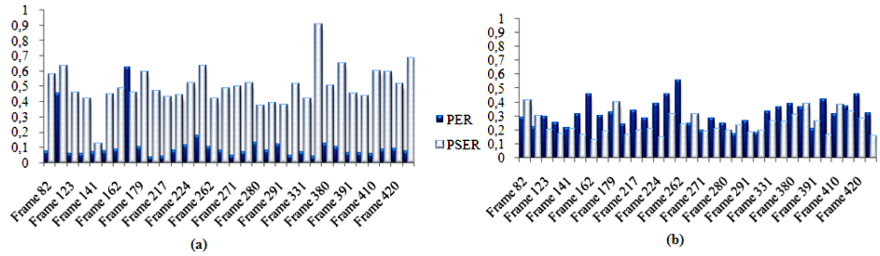

Figure 2: PER and PSER (a) before and (b) after suppressing the cast shadow.

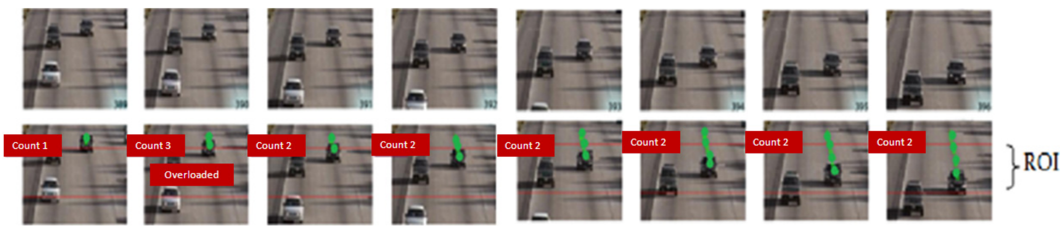

Figure 3: Results of counting and tracking vehicles in HighwayI.