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A New Strategy of Detecting Traffic Information Based on Traffic Camera: Modified Inverse Perspective Mapping

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Abstract:

The development of Intelligent Transportation Systems (ITS) needs high quality traffic information such as intersections, but conventional image-based traffic detection methods have difficulties with perspective and background noise, shadows and lighting transitions. In this paper, we propose a new traffic information detection method based on Modified Inverse Perspective Mapping (MIPM) to perform under these challenging conditions. In our proposed method, first the perspective is removed from the images using the Modified Inverse Perspective Mapping (MIPM); afterward, Hough transform is applied to extract structural information like road lines and lanes; then, Gaussian Mixture Models are used to generate the binary image. Meanwhile, to tackle shadow effect in car areas, we have applied a chromacity-base strategy. To evaluate the performance of the proposed method, we used several video sequences as benchmarks. These videos are captured in normal weather from a high way, and contain different types of locations and occlusions between cars. Our simulation results indicate that the proposed algorithms and frameworks are effective, robust and more accurate compared to other frameworks, especially in facing different kinds of occlusions.

Keywords: Transportation Systems, Hough transform occlusions.

1. Introduction

Recently, accurate and real-time traffic information detection has become a significant problem and early researches attempted to use it in different traffic related applications such as traffic management, traffic control decision making and vehicles scheduling. Practical and useful traffic related information includes, but is not limited to, traffic volume/stream, speed of vehicles, detecting/locating accidents, movements between lanes, or the distance between consecutive vehicles. Given the fact

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that vehicles are of different types with different speeds, various approaches have been proposed and applied to gather such traffic related information so far, including ultrasonic detection methods, electromagnetic induction-based devices, as well as video-based traffic approaches. Regarding ultrasonic sensor-based devices, Kim [1] explains that although they seem economically efficient, their data collection capability is limited as only averaged vehicle speed and/or number of passing vehicles in a certain period can be obtained by ultrasonic based devices. Furthermore, the authors concluded that a high-speed weight-in-motion (HS WIM) equipment which uses loop/piezo sensors is able to obtain comprehensive traffic data such as speed, length, occupancy, axle weight, and vehicle category. However, the main disadvantage of such systems is their relatively high cost and difficult sensor installation as they need to be buried under the pavements.

Video based traffic detection methods, on the other hand, are fairly cost efficient, simple, and more importantly, thanks to the recent technological developments, widely available. Vision based methods seem to be highly promising as they are not only independent of reconstruction of pavements, but also they provide more potential advantages including more flexibility compared to inductive loops as well as larger detection areas. However, using video based detection approaches raises interesting yet difficult problems in the field of image processing. For instance, robust detection algorithms are required as light conditions vary dramatically throughout the day. To overcome such problems, a large amount of computational burden is imposed on the system, which impedes the application of video based algorithms in real-time traffic monitoring system.

1.1. State of the art

In the literature, there are several researches in the field of vision-based traffic information detection. Yuan [2], using a single perspective image taken by a camera at the roadside, proposed a method to detect vehicles and estimate their length, width, height as well as the total number of vehicles. However, their approach is based on remapping images using homogeneous methods, which reduces accuracy result. Wang [3], detected traffic stream and volume using an algorithm based on inverse perspective mapping (IPM). They used IPM to eliminate the geometric distortion related to image sequence. In addition, marking lines in the lane area were extracted by introducing geometric constraints of the road structure. Furthermore, using a background difference method, they extracted the vehicle sequence contours, and, accordingly, to measure traffic stream, they presented two different types of metrics which were vehicles contour area based method and vehicles queue length based methods. Incidentally, traffic stream and volume do not need accurate information and IPM is enough to detect these goals. In [4], Tai proposed an image tracking system based on Kalman filtering. The method is used for

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accident detection, traffic monitoring and vehicle motion detection at road intersections using data provided by a traffic camera. Zhu [5] introduced an automatic traffic monitoring algorithm based on 2D spatiotemporal images. ATV camera mounted above a highway is used to monitor the traffic through two slice windows. Moreover, for each lane, an epipolar image plane and panoramic view image are formed. The proposed method is able to estimate speed, count vehicles, and classify them using 3D measurements. However, the high computational burden of the system makes it difficult to implement it in real-time applications with a reasonable hardware cost. In all the above-mentioned methods, first the difference between the moving vehicles and the background is extracted; afterwards, the images are segmented using edge detection algorithms. Finally, binary images are generated and features are extracted. However, it should be emphasized that the performance of these methods can be exacerbated by the perspective and the geometric properties of the objects in an image which has been distorted. Such distortions reduce the accuracy of the measurement and, in turn, the performance of the traffic information detection algorithms [6]. One of the approaches to eliminate the negative effects of the perspective is to use Inverse Perspective Mapping (IPM). This approach was originally introduced by Mallot[7]. However, Bertozzi[8] reported that IPM re-sampled non-homogeneously in order to produce a new image that represents the same scene as acquired from a different position. In conclusion, in order to develop better intelligent transportation systems (ITS), it is essential to present a method that not only is able to eliminate the perspective from the images, but also is capable of producing an image from the original image, from which real traffic information can be easily and accurately extracted.

Jiang [9] used FIPMA to reduce the computational expense of IPM, but its performance has been changed by the effect of the video quality. It also used the gradient operator to extract edge information of lane markings, such as magnitude and orientation. However, we use Hough transform which is considered a powerful tool in edge linking for line extraction, and is quite insensitive to noise, which is a very good strategy when the video is captured under varying weather conditions.

In this paper, we propose a vision based, real-time traffic information detection algorithm that uses modified inverse perspective mapping MIPM. This method is recommended before any kind of decision about information extracted from the images. Our simulation results verified the better performance of the proposed method compared to similar works in delectability and traceability under different conditions. Perspective and background noise, shadows and lighting transitions are some difficulties which conventional traffic detection methods have to deal with. As indicated in the experimental

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results section, our proposed method performs under these challenging conditions better than those traditional approaches. Ismail [10] presents the development details of a robust camera calibration approach based on integrating a collection of geometric information found in urban traffic scenes in a consistent optimization framework.

Although the real world is 3D, and the image which is taken from the camera belongs to the 3D environment, it is automatically mapped to the 2D world by the camera. This process always implies to lose some information, and the need to search for meaningful features in this 2D environment that may be used to infer 3D properties of the observed objects when video is used for traffic analysis and traffic management.

1.2. Proposed enhancement

In order to achieve our goals in this work, first we eliminated the perspective from the images using a newly proposed Modified Inverse Perspective Mapping (MIPM); afterward, using Hough transform [11],we extracted such structural information as road lines and lanes; then, binary image were produced using a Gaussian Mixture model [12], in a way that the road and the moving vehicles were displayed in white and black colors respectively. As we have to obtain the car area, shadows must be removed, but when using Gaussian Mixture Models, shadows are usually combined with the car area. This is caused by the fact that shadows share the same movement patterns as the vehicle; moreover, shadows demonstrate a similar magnitude of change in intensity as those of the foreground objects. To overcome this issue, we used the Chromacity-based method [13]. Finally, we extracted the required traffic information, such as movement speed of vehicles, area of vehicles (used for classification purposes), types of movement with respect to the structural information of the road and the distance between vehicles. The proposed procedure is tested in good and normal weather conditions and different types of locations; by normal condition, we mean sunny weather at daytime. Results show that our strategy has significant effect in occlusion and in complex sequences. This paper is organized as follows: Section 2 provides the details to extract real traffic information like Modified Inverse Perspective Mapping, Hough transform and Gaussian Mixture Models to detect the vehicle. In section 3, experimental results of the proposed algorithm are presented and compared to other similar methods. Section 4 describes how the results have been validated. Finally, there are concluding remarks in section 5, and comments for the future research are presented in Section 6.

2. Detailed description to extract real traffic information

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The general structure of the proposed traffic information detection algorithm is illustrated in Fig 1.

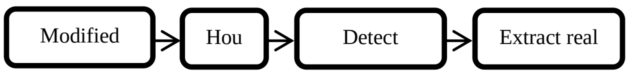

Fig.1: Global description of extract real traffic information

2.1 Description of Modified Inverse Perspective Mapping

Obtaining information about the surrounding environment is a crucial task for biological organisms as well as artificial systems designed for autonomous navigation or driver assistance applications. Inside the camera or the eye, however, on the image plane where the 3D scene is projected, the effects of perspective will complicate most high level information retrieval problems [14]. Inverse perspective mapping (IPM) is a geometrical transformation of the family of re-sampling filters; the initial image is non-homogeneously re-sampled to produce a new image that represents the same scene as acquired from a different position[8].

2.1.1 Removing the perspective effect

IPM method is capable of removing the effect of perspective from the initial image. However, IPM affects the geometric properties of subjects in the newly produced image as it produces a non-homogeneous image. By non-homogeneous, we mean that our obtained image is not regular or easy to analyze the environment and the car area accordingly. In this paper, considering the distance between the subjects and the camera, we proposed the use of a weighting factor which is related to longitudinal and lateral direction. This way, the classical perspective distortion is reduced, and the detect ability and traceability of the objects are maximized using simple but effective image processing strategies.

2.1.2. I → S Mapping

In order to be able to use MIPM transform, one would require the knowledge of the following parameters [8]:

- $W = \{(x, y, z)\} \in E^3$, Which represents the real world in a three-dimensional space (world-coordinate system).
- $I = \{(u, v)\} \in E^2$, which represents the two-dimensional image space (image-coordinate system), which is obtained by projection of the originally three dimensional scene. The I space corresponds to the image taken by the camera, while, considering the flatness of the image, the remapped image is defined as the xy plane of the W space, namely the $S \triangleq \{(x, y, 0) \in W\}$ surface.
- E^3 and E^2 are respectively 3-dimensional (3D) 2-dimensional (2D) Euclidean space.
- each pixel of the remapped image {(x,y,0) ∈ W} assigned to (u(x,y,0), v(x,y,0)) ∈ I

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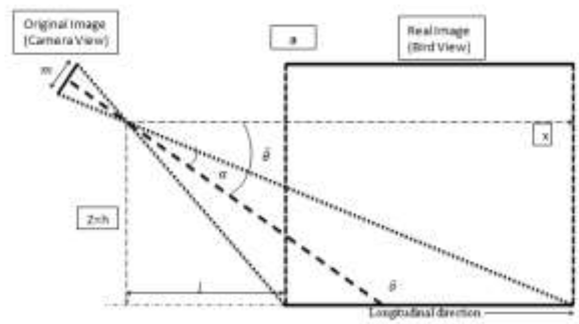
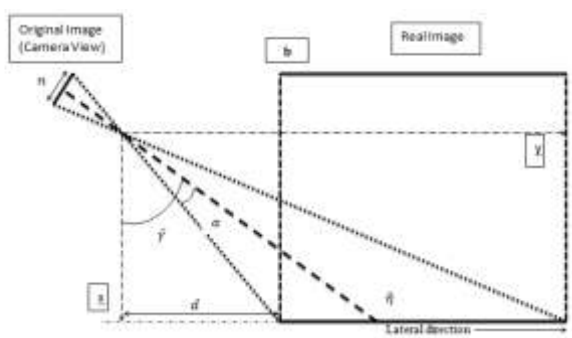
- Viewpoint :position of the camera $C = (l, d, h) \in W$
- Viewing direction: the optical axis $\hat{o}$ defined by the angles below
- $\bar{\gamma}$: The angle which is formed by the projection (defined by $\hat{\eta}$) of the optical axis $\hat{o}$ on the plane z = 0 and the axis x, as illustrated in Fig.2.b.
- $\bar{\theta}$: The angle formed between the optical axis $\hat{o}$ and x axis, as depicted in Fig. 2.a.
- Aperture: the camera angular aperture which is 2α.
- Resolution: the camera resolution which is $m \times n$.



a



b

Fig. 2: a) the zx plane b) Thexy plane in the W space, namely the S surface.

In this paper, to get the mapping from I space to S surface, we used MIPM as formulated in Eq. (1):

$$\begin{cases} x(u,v) = h \times cot\left[(\bar{\theta} - \alpha) + \dfrac{u \times 2 \times \alpha}{m}\right] - l \\ y(u,v) = x \times \tan\left[(\bar{\gamma} - \alpha) + \dfrac{v \times 2 \times \alpha}{n}\right] - d \\ z(u,v) = 0 \end{cases}$$

(1)

2.1.3 **S → Imapping**

Using equation (2), u and v are obtained in I surface, and as we see in Fig (3). The image obtained by MIPM is so much clearer than those by IPM method, this clearness means it can be easily used in computations and calculation of the car area.

$$u(x,y) = \frac{\mathrm{m}}{2 \times a} \times (arccot\left[\frac{x+l}{h}\right] - \bar{\theta} + \alpha)$$
$$v(x,y) = \frac{\mathrm{n}}{2 \times a} \times (\arctan\left[\frac{y+d}{x}\right] - \bar{\gamma} + \alpha)$$

(2)

Although both of the IPM and MIPM remove perspective effect, but in Fig (4) we see that MIPM shows more homogeneous surface than IPM, and we can easily analyze for subsequent calculations. In the real world, cars are 3D, but to compare IPM and MIPM, our assessment is in 2D. The difference between the proposed MIPM and the original IPM can be simply demonstrated in Fig. 3.1. The camera angle with the horizontal axis is 45 degrees, since good results can be obtained by this angle. Different frames in different locations were tested, we have shown four of them (Fig. 3.2).

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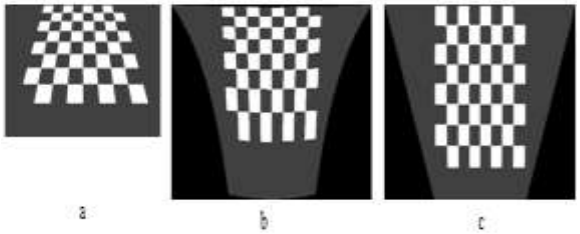

Fig. 3.1: Differences between IPM and MIPM (a) Original image,b) IPM method, c) MIPM method)

Fig. 3.2: Different frames in different locations

2.2. Description of Hough Transform

The Hough transform is commonly used in image processing, analysis and machine learning and in recognizing general shapes as well as geometric known curves, among them, straight lines. This is done by determining local patterns, ideally a point (maximal accumulation), in a transformed parameter space [15].

Much of the efficiency of the Hough transform is dependent on the quality of the input data: the edges must be detected well for the Hough transform to be efficient. Use of the Hough transform on noisy images is a very delicate matter and generally, a denoising stage must be used before. In the case where the image is corrupted by speckle, as is the case in radar or dusty images, our method performs better when detecting lines, because it attenuates the noise through summation.

2.3. Detection of foreground using Gaussian Mixture Models

Detection of moving objects is an interesting field of research. In many vision systems, namely video surveillance and more importantly traffic monitoring, capability of extracting moving objects using a sequence of video is highly crucial and fundamental. To successfully track moving objects, analyze movements of patterns or classify interested objects, it is of utmost importance to reliably perform the movement detection.

2.3.1. Foreground detection methods

Moving objects detection methods can be categorized into three main groups [16]: (i) temporal differencing [17], (ii) optical flow block based obstacle detection [18], and (iii) background subtraction [19,20]. Although temporal differencing can easily adapt to dynamic environments, it is known for the demonstration of poor performance especially in extracting all relevant feature pixels. On the other hand, optical flow is able to detect moving objects while the camera is moving. However, the majority of optical flow methods cannot be used in full-frame video streams in real-time applications, unless specialized high speed hardware is available, because they impose high computational burden on the system. So far, background subtraction has proven to be the category applied most successfully in practice as they can provide the most complete feature data. The basic idea of background subtraction methods is to estimate the background and evolve its estimation frame by frame; then, it uses the differences between the current frame and the current background model to detect moving objects. However, it should be noted that it is highly sensitive to dynamic scene changes caused by lighting and other extraneous events like bad conditioned weather.

2.3.2. Gaussian Mixture model (GMM)

In the field of image processing, many different researches have been carried out so far with the main purpose of presenting an efficient and reliable background subtraction. Considering the statistical features applied to constructing the background model, most of the methods proposed in this field can be categorized into methods based on minimum and maximum values, median value, single Gaussian, multiple Gaussians [21] (also known as Gaussian Mixture model (GMM)), etc. Among subtraction methods, GMM is known to be the most accurate approximation while processes practical pixels. One single adaptive Gaussian per each pixel will be enough, if each one of the pixels resulted from a single surface with lightings that are fixed or slowly changing. However, practically speaking, such conditions do not hold in frames as multiple surfaces often appear in a particular pixel and also the lighting of the frames fairly changes. Consequently, single Gaussian methods cannot be used and GMM is required for detecting the model of the background. Each one of Gaussians indicates the expectation that samples of the same scene point are likely to display Gaussian noise distribution function. On the other hand, multiple Gaussians indicate the expectation that more than one process type may be detected over a period of time. Applying multiple Gaussians used to impose high computational burden on the system. However, this is not the case nowadays since researchers have proposed several simplifications to reduce computational complexity which makes them suitable for real-time applications [21]. Moreover, multiple Gaussians approaches are desirable methods as they require much less storage capacity due to the fact that, unlike other classes of methods (such as median value methods), they do not need to store numerous preceding frames. GMM based methods are able to successfully handle gradual lighting changes as they slowly adjust parameters of the Gaussians [22-24]. Additionally, GMM based methods are also capable of handling multimodal distributions caused by real world application issues such as shadows, swaying branches, secularities, computer monitors, which are generally ignored in computer vision literature. As an example, holes created in objects or still left in that stop moving are taken into account as the background model, which benefits subsequent detection.

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Moreover, when the background reappears in the image, GMM responds fast and recovers quickly. Finally, GMM automatically creates pixel-wise threshold which is generated to flag potential points as moving object.

2.3.3. Shadow detection

Generally speaking, Gaussian Mixture models suffer from a major disadvantage: shadows are sometime detected as the foreground. This phenomenon is caused by the fact that shadows demonstrate movement patterns that are the same as the main moving object and also represent a magnitude of intensity change similar to the foreground objects. To overcome this issue, several methods have been proposed in the literature such as Chromaticity-based methods [13], Geometry-based methods [26], Physical methods [25], Large region (LR) texture-based methods [28], and Small region (SR) texture-based methods [27].

2.3.4. Chromaticity-based method

In order to have successful application of chromaticity methods it is of utmost importance to choose a color space with a separation of intensity and chromaticity. It has been proven that in order to have a robust shadow detection algorithm, some color spaces are suitable, such as HSI, c1c2c3 and normalized RGB. In this study, we have chosen the HSI approach introduced by Cucchiara [6]. This selection provides a natural separation between luminosity and chromaticity for our proposed method, and leads to the better detect ability of our method. It should be noted that Cucchiara-based shadow detection approach has been successfully applied in surveillance applications. As mentioned earlier, value (I) is a measure quantifying intensity; thus, values of (I) related to pixels in the shadowed part should be lower than those of the pixels in the background. Following the chromaticity cues, a shadow on the background does not show a change in its hue (H). It should be mentioned that the authors observed that if the shadow was cast on a point, the saturation (S) of the point would decrease. To sum up, we suggest that a pixel p should be detected as a part of a shadow if the following three conditions are satisfied:

$$\beta_1 \leq \left({F_p^I}/{B_p^I} \right) \leq \beta_2$$

$$\left(F_p^s - B_p^s\right) \leq \tau s$$

$$\left|F_p^H - B_p^H\right| \leq \tau H$$

Where F and B represent the component values of HSI for the pixel position p in the frame (F) and in the background reference image (B), respectively. β_1, β_2, τs and τH represent thresholds that were optimized empirically.

We have tested with several thresholds, obtaining the better results in all the tested sequences with values around the following ones:

$$\beta_1\text{=0.31}$$

$$\beta_2\text{=0.57}$$

$$\tau s\text{ =0.1}$$

$$\tau H\text{ =0.5}$$

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3. Testing Results

3.1. Inherent geometry characteristic

To obtain real information from the original images taken by traffic camera, it is better to remove perspective from images. To do so, we used the previously commented method called Modified Inverse Perspective Mapping (MIPM). When using MIPM to remap images, geometric features of the road can be easier and more efficiently extracted from the remapped picture compared to the IPM version (fig. 4).

Fig. 4: a) Original image with perspective effect,b) Remapped image that removed ,erspective with IPM,c) Remapped image that removed perspective with MIPM

Images used in Fig 5 were taken by traffic camera under controlled conditions. Our scene is normal condition, and normal condition means sunny weather and daytime, which causes the moving of the vehicles to become transparent. It should be mentioned that vibrations of the camera were decreased to avoid its negative effects on the quality of the images. Images were of the resolution 640×480 so that the volume of information was reduced while the quality of the image remained suitable.

3.2. Locating the lane area

It is required to locate lane areas so that we become able to detect vehicles queue in video frames. In this work, we used Hough transform due to its structure in considering locations and to detect straight lines which were colored white. In the sample image, no vehicle was included (Fig. 5.1).Actually in this figure, lines are not straight, but Hough transform can be applied for curve detection if we know little about the location of a boundary, which its shape can be described as a parametric curve (e.g., a straight line or conic). We know the results will not be affected by gaps in curves and by the noise. Road lines chosen to define lane areas (Fig. 5.2).

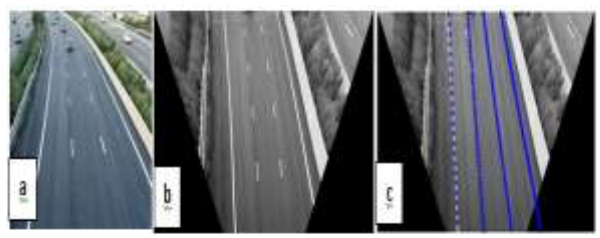

Fig. 5.1: a) Original image, b) Removed perspective with MIPM,c) Detect Lines

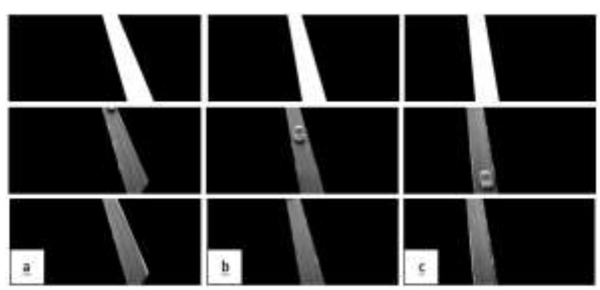

Fig.5.2: Define lane area,a) lane1,b) lane2,c) lane3

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3.3. Detection of vehicles

To determine if a certain pixel is a part of the background or foreground, Gaussian Mixture Models (GMM) compares a color or grayscale video frame to a background model already calculated. Afterwards, GMM defines a foreground mask which will be used to detect vehicles (Fig. 6). Test results indicate that, using the presented methods, one can extract real properties of the vehicles such as area, width, length as well as the distance between the vehicles. However, to improve the results, it is much better to remove noise from images, such as the shadow detected by GMM.

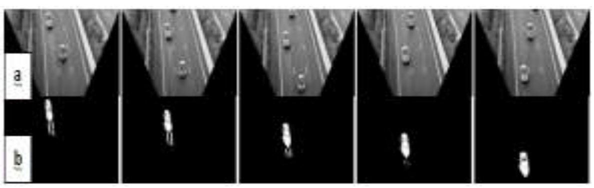

Fig.6: Detection of vehicle in lane1,a) Remapped by MIPM,b) Detected vehicle in lane1 by GMM

3.4. Removing of shadows

Proposed method works based on a modified version, chromacity information was applied to create a mask of candidate shadow pixels, followed by the gradient information to remove foreground pixels that were incorrectly included in the mask. In our work, to remove shadows with the chromacity-based method, first, space color of the images should be converted from RGB to HSI. Using equations 3, 4 and 5 and differences between the shadow and the vehicle in images, we extract boundary for hue, saturation and intensity (Fig. 7).

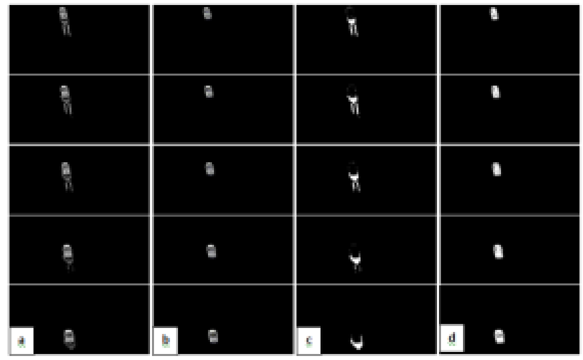

Fig.7: Removal of shadows with the hromacity-based method,a) Results of dot product between original images and binarry images,b) Removal of shadows in the original images ,c) Shadows are detected,d) Results of the difference between the shadow images and the binary ones

3.5 Detection and tracking of the position of the vehicles on the road

To detect the position of a certain vehicle on the road, first, all objects of the images were labeled; then, the geometric center of each one of the vehicles was determined. Each geometric center is considered as one vehicle (Fig. 8.1). Moreover, the path of a vehicle can be obtained by aligning its geometric centers in consecutive frames (Fig. 8.2).

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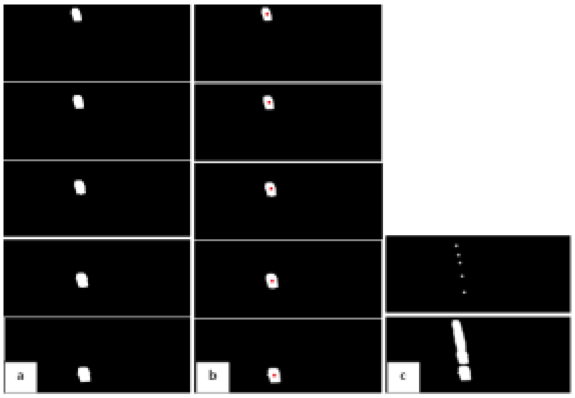

Fig. 8.1:a) Binary images ,b) Geometric centers (red points),c) Aligning the geometric centers (white points*)*

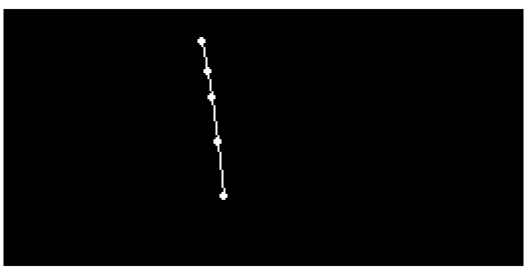

Fig. 8.2: Path of vehicle

4. Results and validation

In this section, several kinds of traffic volume are considered as low traffic, high traffic, highway, urban, interurban and intersection. Also, different testing sequences which contain normal class of cars, urban traffic with small and large vehicles, selected to test our method. Underneath, the performance of the proposed MIPM is compared with that of the conventional IPM. For this purpose, first, different types of cars in different locations were randomly selected. We applied both the IPM and MIPM methods to the images. Then, using Gaussian Mixture Model and Chromacity-based Method, vehicles areas were calculated. This was used as a measure to evaluate the performance of IPM and MIPM. Table 1 and diagram 1 show the obtained results related to a certain vehicle. Vehicles areas were calculated using Gaussian Mixture Model and Chromacity-based Method to evaluate the performance of IPM and MIPM. So, Eq.6 is used to normalize the Vehicle's area for different sizes of the vehicles. In other words, the area of the vehicle compared to the measured one in its first detected image, the vehicle base area.

$$Area\ Normalization = \frac{area\ of\ vehicle}{Base\ area\ of\ vehicle}$$

N.Frame	1	2	3	4	5	6	7	8	9	10	11	12	13	14
MIPM	1	1.04	1.03	1.06	1.09	1.06	1.07	1.06	1.14	1.13	1.17	1.19	1.21	1.21
IPM	1	1.04	1.05	1.06	1.12	1.13	1.14	1.3	1.34	1.34	1.41	1.46	1.47	1.66
N.Frame	15	16	17	18	19	20	21	22	23	24	25	26	27	28
MIPM	1.24	1.20	1.25	1.27	1.24	1.32	1.26	1.29	1.33	1.36	1.36	1.38	1.44	1.41
IPM	1.72	1.69	1.9	1.89	1.92	2.19	2.10	2.14	2.44	2.65	2.64	2.87	3.29	3.25
N.Frame	29	30	31	32	33	34	35	36	37	38				
MIPM	1.42	1.43	1.45	1.49	1.50	1.50	1.54	1.56	1.58	1.57				
IPM	3.62	3.80	3.70	4.46	4.67	4.70	5.38	5.77	5.71	7.12				

Table 1: Car area variation along with its direction using the two methods, IPM and MIPM

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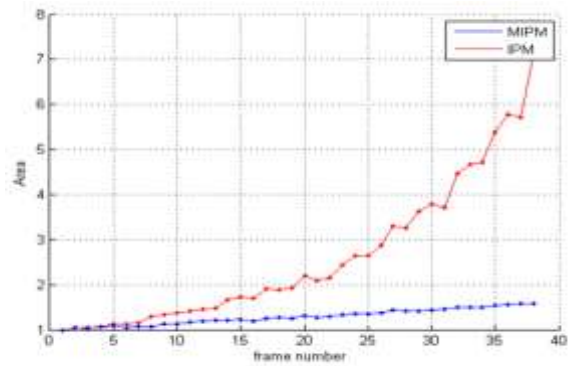
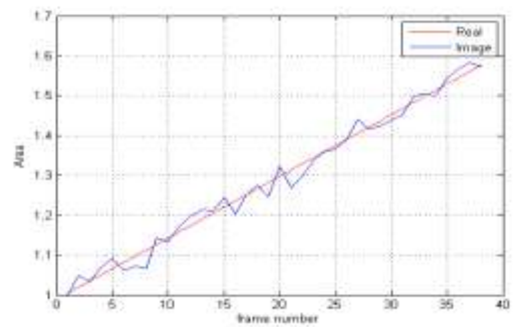
Variations of car areas along with their directions (fig 9.a and table 1) illustrate that MIPM is not only able to successfully remove perspective with a suitable scale, it can also create better estimations for the moving objects. Accordingly, it can be inferred that MIPM outperforms IPM as when we use MIPM:

- The area of the vehicle is constant in each location.
- The measured distances between vehicles are more accurate.
- The measured distances between the vehicle and camera are more accurate.
- The measured width of the road and the vehicle is more accurate.

To further evaluate the performance of IPM and MIPM, the measured areas of different cars in different locations were compared with the reported areas by the manufacturing companies. Accordingly, every square millimeter was considered as a pixel, then, formula 6 was applied to normalize the results. Considering the position and direction of the vehicle, we measured the vehicle's area in the images and compared them with actual areas. The results relating to one of the vehicles are illustrated in fig 9.b.



(a)



(b)

Fig 9:*(a) Car area variation along with its direction using the two methods: IPM and MIPM,b) Comparison of actual vehicle's area and obtained area from image considering position and direction of the vehicle: Results indicate that areas measured using the presented MIPM method are for 90% of the tested cars are closer to the actual areas with* $R^2>0.98$.

As shown in above figures, MIPM performance is comparable with IPM in the first frames, but it is different in the following ones.

Table 2 shows our big sizeable data set on different locations and different sequences.

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Table 2: Data set Results on different locations with success Rate

	Testing sequence	*Vehicle detection*	*Line detection*	*Shadow removal with vehicle detection*	*Success Rate*
Low Traffic	*18* *10* *5*	99.8%	*99.7%*	*98%*	*99.1%*
High Traffic	*15* *7* *21*	*95.2%*	*99.2%*	*97.2%*	*97.2%*
Highway	*8* *12* *21*	*97%*	*97.9%*	*99.1%*	*98%*
Urban	*20* *6* *15*	*97.8%*	*98.9%*	*96.5%*	*97.7%*
Interurban	*5* *9* *14*	*96.5%*	*98.3%*	*99.3%*	*98.03%*
Intersection	*4* *12* *22*	*98.2%*	*99.5%*	*88.9%*	*95.5%*

We used different condition such as occlusion, shadows and lighting transitions and different sequences in Table 2 to measure success Rate of our proposed method. For this purpose, our method handled for several times, then best success Rate considered as Table values. According to the table 2, the average rate of vehicle detection is 97.41%, and line detection rises to 98.91%. It additionally indicates that shadow removal is good enough to provide vehicle detection with an average rate of 96.5%.

The numerical results obtained with our method are presented in the above Table. The detection results for different data sets show that our method is effective. The occlusions of cars in the video sequences are generally as many as that in the static image set. Note that the detection rate on video is computed in a ground-truth way: we have only labeled 10 frames per second from the video. Then we label the frames manually. Finally we compare the detection result and the labeled data of this frame to compute the detection rate as Success Rate. In our method, the Testing sequences as follows are eliminated: 1) too few or too many occlusions in the image 2) the majority of vehicles in the image are not front-view 3) the discriminability of the image is low, e.g., the image is blurred or the vehicles are too distant in space. Using an image-label tool, we created positive samples from these images. The diversity of occlusions over the positive samples are noticeable, i.e., the positive samples with different occlusion situations should be included into the training set and the numbers of samples representing each situation are as well almost identical to the true distribution of this situation in the real world. However, it's difficult to obtain this information. So, in our method, the numbers of each occlusion are set equally. We treat the occlusion situations as three types for cars: 1) two or three successive cars occlude one by one in the same lane 2) one car is behind a car in the same lane 3) one car is occluded by the vehicle driven towards the same lane. The structural information, like lanes or traffic markings, are sometimes badly marked or even are hard to identify in the presence of harsher weather conditions. In Table 3, an analysis of the correct rate is considered. We used false positive and correct detection obtained in car and lane detection for our comparison. For this purpose, pixel wise evaluation is used to compute these parameters. Additionally, car detection and lane detection are building blocks that considered for better accuracy of this method. Considering our algorithm in viewpoint of time consuming and detection rate, our method outperforms others as indicated in Table 3 and 4.

TABLE 3: analysis of correct rate

Data set	Frames	Detected	Boundary	Correct rate	False rate	Correct lane
Low Traffic	600	571	540	95.3 %	5.21%	98.7 %
Interurban	1220	1200	1201	97.4 %	3.87%	98.6 %
Intersection	1000	1020	1120	91%	11.3%	95.7 %

TABLE 4: Comparison with other Methods in KITTI dataset

Method	P1	P2	P3	Runtime
MIPM	94.2%	96.4%	89.3%	0.031s
IPM	92.3%	95.1%	90.1%	0.021s
Proposed method	97.2%	97.3%	92.3%	0.022s

5. Conclusions

In this research, we have proposed a robust method for extracting real information from traffic cameras. The research focused on several different issues, namely removing perspective, automatic locating of lines and lanes, vehicle detection and extracting features of the vehicles.

As the main contribution of this research, we have proposed a method to remove perspective

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without any harmful effect on the real information. Experimental results indicate that the proposed method, called Modified Inverse Perspective Mapping (MIPM), was not only simple and straightforward, but it was also more accurate compared to the state-of-the-art. However, the proposed method was not tested under camera vibrations and poor lighting conditions. Therefore, in our future studies, we will work on generalizing the proposed framework to become robust against poor environmental conditions. Moreover, to generalize our framework to 3D information extraction, we will use two cameras instead of one to remap 2D space to 3D.

6. Future Work

From the results obtained in the previous sections, despite having the same information, the proposed MIPM method is of better clarity and transparency compared with the IPM method. However, we have to improve our method in such a way that it can be applied well under poor weather conditions. In the future, we can propose a solution for the problem.

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