Video-Based Automatic Incident Detection for Smart Roads: The Outdoor Environmental Challenges Regarding False Alarms

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***Abstract*—Video-based automatic incident detection (AID) systems are increasingly being used in intelligent transportation systems (ITS). Video-based AID is a promising method of incident detection. However, the accuracy of video-based AID is heavily affected by environmental factors such as shadows, snow, rain, and glare. This paper presents a review of the different work done in the literature to detect outdoor environmental factors, namely, static shadows, snow, rain, and glare. Once these environmental conditions are detected, they can be compensated for, and hence, the accuracy of alarms detected by video-based AID systems will be enhanced. Based on the presented review, this paper will highlight potential research directions to address gaps that currently exist in detecting outdoor environmental conditions. This will lead to an overall enhancement in the reliability of video-based AID systems and, hence, pave the road for more usage of these systems in the future. Last, this paper suggests new contributions in the form of new suggested algorithmic ideas to detect environmental factors that affect AID systems accuracy.**

***Index Terms*—Automatic incident detection (AID) systems, glare detection, rain detection, shadow detection, snow detection.**

I. Introduction

As modern cities grow today, they face worsening congestion due to the increased volume of traffic on roads. Intelligent transportation systems (ITS) have emerged as a cost-effective manner to increase the efficiency of the existing infrastructure. According to Wang *et al.* [1], ITS can be defined as "those systems utilizing synergistic technologies and systems engineering concepts to develop and improve transportation systems of all kinds." Video-based automatic incident detection (AID) systems are considered to be a main component of ITS, and they are increasingly deployed in modern cities.

Transport Canada released an ITS plan in November 1999 to spearhead the deployment of such systems [2]. The stated goals for this initiative were primarily to promote transportation safety and to improve our quality of life by making transportation smarter and more productive.

The United States has had its own initiative since 1991 when the Intermodal Surface Transportation Efficiency Act was signed [3]. With many of the same objectives, the program was designed to facilitate the deployment of technology to enhance the efficiency, safety, and convenience of surface transportation, resulting in improved access, saved lives and time, and increased productivity.

As a result of both initiatives, many ITS are deployed in North America today, such as GuideStar in Minnesota, TranStar in Houston, TX, and COMPASS in Toronto, ON, Canada, and in the Dalls-Ft. Worth, TX, area. Europe has also seen extensive deployment of similar systems throughout European Union roadways [4]. Many traffic management systems do not have highly effective AID with high accurate detection rates and acceptable low false alarm rates, but rather rely on human operators to monitor cameras. This is not to say that the demand for AID does not exist. There is, in fact, a burgeoning interest in such technologies, particularly from cities that have an existing closed circuit television infrastructure for monitoring transportation links.

This paper focuses on video-based AID, where the system is able to detect any traffic abnormalities on a given section of a roadway from a live video feed. Examples of such abnormalities would include vehicles stopping where they are not supposed to, vehicles reversing (i.e., wrong-way driving) or, otherwise, driving the opposite direction of traffic flow, vehicles dropping cargo or objects on the road surface, and vehicles involved in collisions.

Although many may argue that cell phones can provide faster incident detection than cameras, a well-designed AID system will be more efficient at deploying resources to a potential incident. An emergency operator may receive any number of calls with regard to a particular incident, resulting in poor efficiency and reliability. In contrast, an AID system is able to detect these incidents and automatically notifying authorities in a very expedient manner, allowing ambulances, fire trucks, and police to reach the scene of an accident faster than before. These systems can be also used to alert traffic users to the current status of roadways, allowing them to dynamically manage traffic lights to facilitate traffic congestion.

The technology of video-based AID systems is still relatively new. As with any new technology, there are problems associated with video-based incident detection. The most critical problem with such systems is the high rate of false alarms that are generated by these video-based AID systems, which can be up to 60%–80% of total alarms. The frequency of these false alarms is due to the use of AID systems in uncontrolled outdoor environments, where weather has a huge impact on the reliability of the detected alarms. In many cases, environmental factors, such as the presence of static shadows, snow, rain, or glare, are likely to trigger a false alarm.

This paper presents an extensive review of the different work done in the literature to detect outdoor environmental factors, namely, static shadows, snow, rain, and glare. This review is most beneficial in identifying the current progress to detect such environmental factors and, hence, enhance the performance and the reliability of video-based AID systems.

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Based on the presented review, this paper will highlight potential research directions to address gaps that currently exist in detecting outdoor environmental factors. This can lead to an overall enhancement in the reliability of video-based systems and, hence, pave the road for more usage of these systems in the future. Last, this paper suggests new contributions in the form of new suggested algorithmic ideas to the detection of environmental factors affecting AID systems.

The remainder of this paper is organized as follows. Section II describes the different types of problems that are associated with the use of AID systems in an outdoor environment. Section III presents a statistical evaluation of using two different AID systems in an outdoor environment to show the seriousness of the false alarm problem. In Section IV, a description of the survey's objectives and methodology is presented. Sections V–VIII present a survey on the state of the art and literature review, as well as proposed algorithmic ideas for the detection of stationary shadows, snow, rain, and glare, respectively. Section IX presents some future research areas. Last, Section X draws the conclusions.

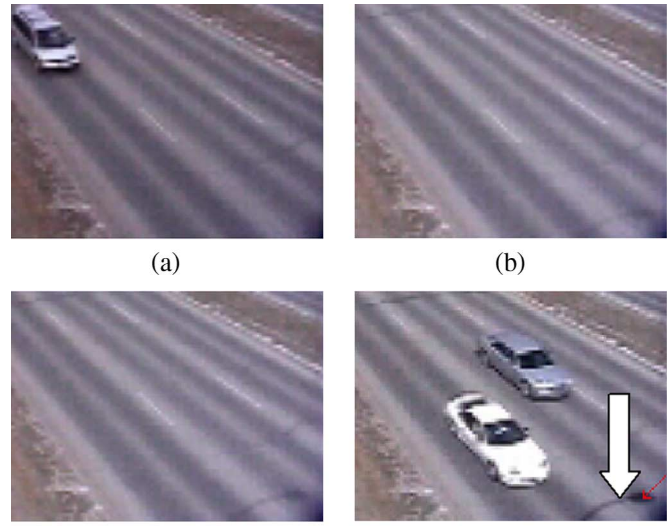
II. Problems of Operating AID Systems in the Outdoor Environment

A. Overview

Video-based AID systems are increasingly being adopted to monitor roadways for traffic incidents without the need for human operators. These systems, although proficient in detecting real incidents, are not so adept at discriminating these from ordinary scene changes due to external environmental factors, resulting in a high percentage of false alarms. False alarms stem from issues such as the appearance of stationary shadows on roadways, changes in the scene due to the presence of snow on roadways, the presence of rain in the scene, and the presence of static glare on roadways. As a result of these outdoor environmental factors, many false alarms are generated, lowering the overall accuracy, reliability, and confidence in the use of AID systems. This results from the fact that many AID systems have not been designed to properly anticipate complex outdoor conditions. The corresponding high false alarm rate limits the efficiency and use of AID systems because of additional AID system operator costs and potential compensatory upgrades. In addition, in environments with rapid changes in weather conditions, false alarm rates significantly reduce the performance of AID systems and, at times, render them useless.

The correct detection rate of AID systems also plays a fundamental role in the usage of AID systems in the outdoor environment. Many outdoor environmental factors, such as illumination problems and fog, may have a huge impact on the correct rate detection of an AID system. However, the focus of this paper is not to increase the detection rate for AID systems but to minimize false alarms. Hence, environmental factors, such as illumination problems and fog detection, will not be addressed in detail. Only as an example, fog detection research is briefly discussed in the following.

The research in [55] proposed fog detection and warning system along with a description of fog climatology and the approach taken for sensor location. In [56], a fog detection system was built in Holland using visibility sensors to monitor the weather conditions. The report presented in [57] is aimed at examining the ability of meteorological satellites to detect fog and provide useful information to weather forecasters or transportation officials for the purpose of local warnings and advisories. The ability of the Geostationary Operational Environmental Satellite (GOES) techniques to detect fog was evaluated in this report. This report also showed that some technological improvements are scheduled to be implemented on GOES that should help with fog detection and advisories.



(a) (b) (c) (d)

Fig. 1. False alarm that is generated by an AID system due to the presence of a static shadow in the lower right-hand corner of the image. A false alarm is not generated until (d), when the shadow becomes clearly defined.

There are a number of commercially available products that have attempted to deal with different environmental effects such as shadow, glare, and fog. Companies like Econolite and Citilog offer commercial AID systems that have had varying degrees of success with respect to false alarms generated by weather conditions. However, with the limited experience of the researchers that are associated with this paper with regard to commercially available systems, and as the survey in this paper is limited to published papers and patents, and not to commercial products (see Section IV for details), we will not describe in detail the commercial products.

B. False Alarms Due to Shadows

The presence of stationary shadows arises due to changes in the scene's lighting conditions. For example, when the sun angle changes, it causes the shadow of a stationary object, such as a tree or a street lamp, to be projected on the roadway until the shadow becomes clear enough on the roadway for the AID system to notice it. A video-based AID system may interpret this new appearing shadow as an incident and, hence, trigger an alarm. Fig. 1 shows screenshots of a false alarm due to shadow. The problem becomes even more challenging when the object of which the shadow is being projected does not appear in the scene.

C. False Alarms Due to Snow

The presence of snow in the scene can also trigger a false alarm. Usually, when the road is covered of snow, and there is a moving vehicle passing on the snowy roadway, the vehicle would change the shape of the snow, e.g., in the form of a snow trail behind the moving vehicle. An AID system will perceive the changes in the snow shape as a moving object that has stopped and, hence, trigger an alarm. Fig. 2 shows snow trails behind a moving car. The snowplow can be seen in Fig. 2(b) and (c). The corresponding false alarm is generated in Fig. 2(d).

D. False Alarms Due to Rain

Rain causes a road to become drenched and covered over with a layer of water. An example of the tides of foam washing over the road

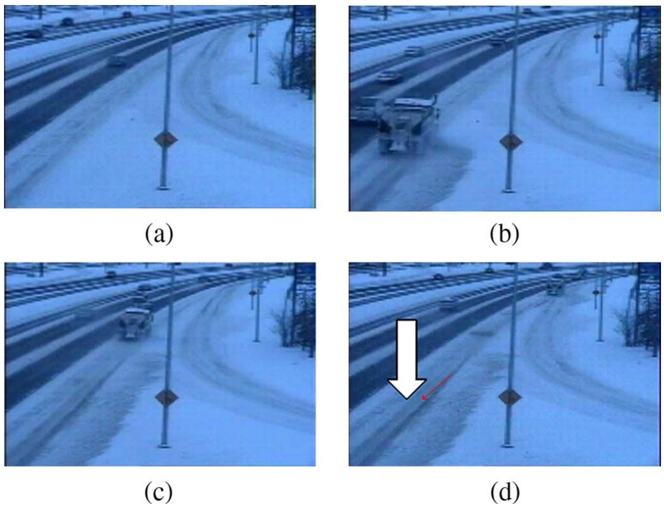


Fig. 2. False alarm that is generated by an AID system due to the snow trail left by the snowplow. (b), (c) Snowplow. (d) Corresponding false alarm.

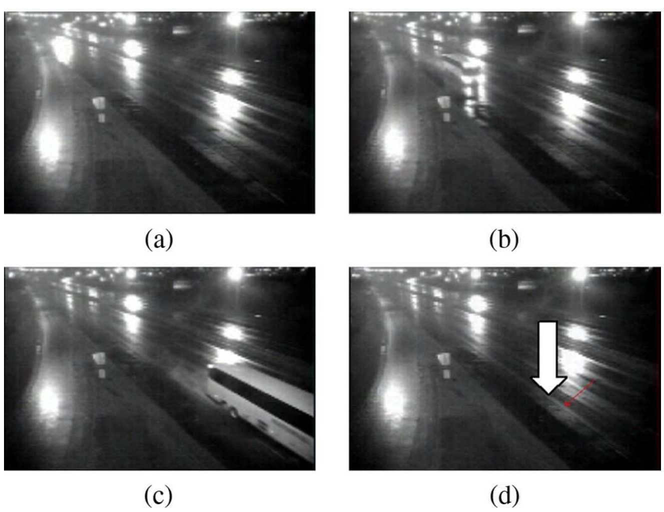


Fig. 3. False alarm that is generated by an AID system due to water foam that is generated by the fast-moving vehicle. (c) Vehicle. (d) Resulting false alarm.

when a vehicle is passing is shown in Fig. 3. The tides of the water from the rain on the roadway may set an alarm in AID systems, as seen in Fig. 3.

E. False Alarms Due to Glare

Glare appears at night when the road is wet, and the street lamps or vehicle headlights are turned on. The road reflects the light from street lamps or vehicle headlights, causing glare on the roadway. The glare caused by headlights will move with the vehicles and is called moving glare. However, the street lamps are stationary, and the glare caused by the lamps is called static glare. In traffic monitoring using video-based AID systems, moving glare is only a problem when it reflects off the roadway causing unpredictable illumination. However, the direct glare from a vehicle's headlights follows the vehicle's movements and does not trick most commercial systems to trigger a false alarm. Hence, moving glare will not be discussed in this paper. However, it is understood that moving glare can cause false detection in incident detection systems where detection of wrong-way vehicles (e.g., ghost

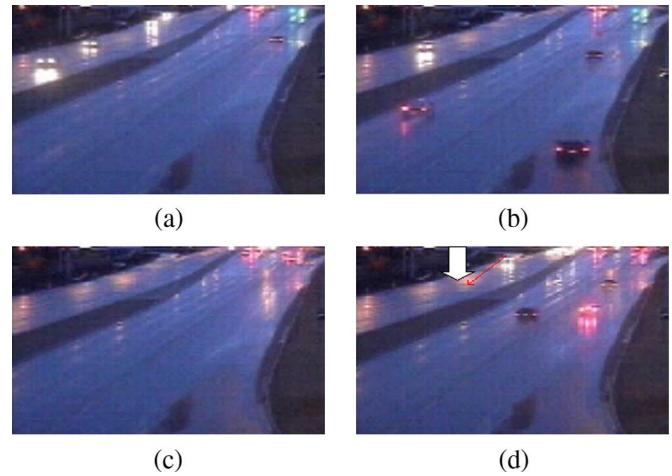


Fig. 4. False alarm that is generated by an AID system due to glare caused by street lamps. As the glare reflected on the roadway becomes more clearly defined, a false alarm is generated in (d).

runners) is implemented. As for the static glare, when it becomes stationary and bright enough after a period of gradual brightening on the wet road, the system often mistakenly detects this glare as moving vehicles that have stopped and flags them as incidents, thus generating false alarms. This situation can be seen in Fig. 4.

III. Evaluation of False Alarms for an AID in Outdoor Environment

The problem of false alarms that are generated when operating an AID system in an outdoor environment is a serious one. The seriousness of this problem can be explained based on the fact that as the number of false alarms increases, the reliability of the AID system decreases, and hence, the users of the AID system will stop, depending on the results provided by the AID system and eventually may potentially stop using it. Imagine a situation when a user is receiving alarms of incidents that require emergency intervention, out of which about 80% are false alarms. Furthermore, future users that were thinking of using an AID system in an outdoor environment will reconsider, as the system will not provide them with the accuracy they require.

The authors have evaluated two real deployed AID systems, which we will call Sys1 and Sys2 for the reason of not disclosing information that can harm their manufacturers. The two systems were installed and are fully operational in two different cities, which we will call City1 and City2. These two systems are installed as part of the Traffic Management Centers (TMCs) of City1 and City2, and we were allowed to analyze their performances.

The first system (Sys1) was deployed in City1 and was installed in a tunnel to monitor the traffic in it and provide alarms of incidents that can affect the traffic flow in the tunnel. The analysis of the false alarms for Sys1 showed that the percentage of false alarms is about 25% of the total generated alarms. The main source of false alarms was static shadows, and it contributed to about 90% of the total false alarms, whereas there were about 10% of the false alarms due to other factors. The 25% false alarms are considered to be large, particularly in a tunnel monitoring system, where many of the environmental conditions (e.g., lights) are well controlled. There was big interest in enhancing the reliability of the AID Sys1 to reduce this percentage of false alarms.

The analysis of the second system Sys2 was performed over a 1-year period using 3915 incidents (true and false incidents) that were

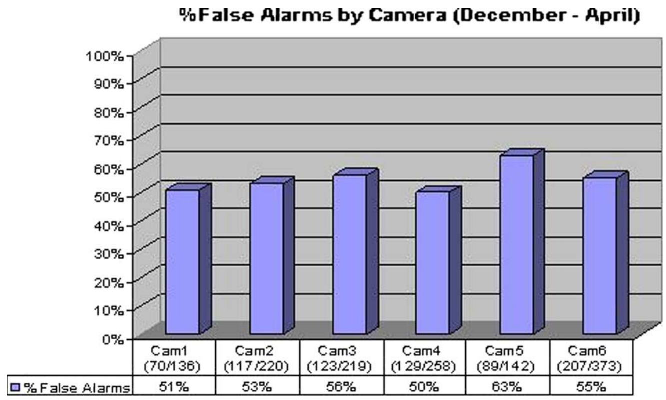


Fig. 5. Percentages of false alarms in Sys2 during the wintertime.

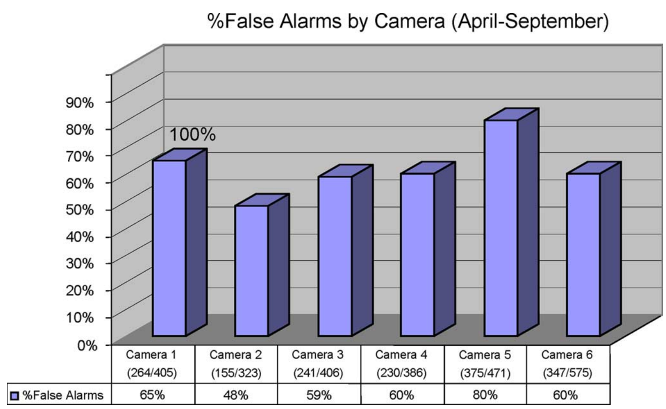


Fig. 6. Percentages of false alarms in Sys2 during the summertime.

TABLE I
CONTRIBUTION OF DIFFERENT ENVIRONMENTAL FACTORS TO THE CREATION OF FALSE ALARMS

	Winter	Summer
Static Shadows	25%	38%
Snow	23%	0%
Rain	5%	29%
Glare	25%	12%
Others	22%	21%

detected using the second AID system (Sys2). The 3915 incidents that were detected using Sys2 were fully analyzed to identify alarms that were falsely triggered and to identify the different sources that have caused these false alarms to be triggered. The AID system Sys2 used six cameras to monitor traffic in different parts of City2. The results of the analysis showed that the different cameras had false alarms that ranged from 48% for the best performance to 80% for the worst performance. Figs. 5 and 6 show the percentages of false alarms for the six cameras used by Sys2 to monitor the traffic in City2 during the winter period (December–April) and the summer period (April–September), respectively.

The analysis to identify why such false alarms are created showed that there were four main sources of environmental conditions that can cause a false alarm to be triggered, namely, shadow, snow, rain, and glare. The percentages of contribution of each of these causes to the total false alarms varied according to whether Sys2 was used in the winter or in the summer. Table I shows the contribution of the different environmental factors to the false alarms triggered by Sys2 during its operation over a 1-year period in City2. From the outcome of this analysis regarding the sources of false alarms, the authors have decided to focus their survey on the main four alarms sources (shadow, snow, rain, and glare) that contribute to about 80% of the total false alarms.

IV. OBJECTIVES AND METHODOLOGY

The survey in this paper was conducted to target the following objectives.

1) Identify the different approaches and methodologies that explicitly address the detection of specific environmental factors (shadow, snow, rain, and glare) that can have great effect and influence on the reliability and the accuracy of video-based AID systems.
2) Identify the gaps that exist in the literature for detecting such environmental factors that can be considered as new research directions for enhancing the reliability of AID systems.
3) Propose solutions in the form of algorithmic ideas for detecting outdoor environmental factors that partially benefit from other approaches that are not directly targeting the detection of outdoor environmental factors.
4) The survey in this paper is limited to published papers and patents because
   a) commercial companies do not disclose sufficient technical information about their products to be included in this survey;
   b) this survey is not intended to publicize for commercial products, but rather focuses on the technical algorithms and techniques that are not available in case of these commercial products.

The survey presented in this paper starts by identifying those approaches that explicitly target the detection of outdoor environmental factors. The outcome of this step, to our surprise, revealed a very limited number of approaches. There were huge gaps that need extensive research efforts. Based on the survey of current approaches, solutions to detect outdoor environmental factors are proposed. These solutions partially benefit from other popular approaches that are not directly applicable to the detection of outdoor environmental factors (e.g., edge detection). The proposed solutions can be used in new algorithms for detecting outdoor environmental factors.

The detection rate of an AID system plays also a fundamental role in the usage and the calibration of AID systems. Indeed, to calibrate an AID system, the best compromise between the false alarm rate and the correct detection rate is often searched. In the contrary case, if the focus is only on the false alarm rate, it is enough to slacken the thresholds of detection algorithms to reduce the false alarm rate. However, from our experience with several municipalities and authorities, they get very concerned if the detection rate is not at its highest level, even at the expense of having a higher false alarm rate. Therefore, we assume the situation of having a high detection rate without adjusting the thresholds to reduce the false alarms. Moreover, the focus of this paper is not to increase the detection rate for AID systems but to minimize false alarms. Hence, environmental factors, such as illumination problems and fog detection, were not addressed in detail. Only as an example, fog detection research was briefly discussed in Section II.

V. STATIONARY SHADOW DETECTION

Little research has been done on stationary shadow detection compared to moving shadow detection. Therefore, it is somewhat useful to take ideas from moving shadow detection and transfer them over to stationary shadow detection. Furthermore, the discussion of moving shadows will be limited to moving vehicles, as research on moving shadows due to other sources is not considered to be as significant.

In [5], a method is presented of using a pixel's brightness and normalized red, green, and blue (RGB) color components to perform moving shadow detection. A pixel is assigned a background, foreground, and shadow probability based on a color feature, and this probability is used as the *a priori* probability when evaluating the next color feature. Each color feature probability is evaluated by using the mean and the variance of a moving shadow database.

In [6], moving shadow detection is accomplished with analysis of the hue–saturation–value (HSV) color space for the current image and the background, and the generated shadow map is inputted into the statistical and knowledge-based object detector (SAKBOT) system, which is developed for shadow suppression. The method of background generation was only referenced and not discussed since this was not the focus of this paper. To classify pixels as moving shadows, the value ratio of the current image and the background, the saturation difference between the current image and the background, and the absolute hue difference of the current image and the background are used. These three conditions require four experimentally derived thresholds that vary in response to the sun's position during the day. Such a dependence on solar position impedes the choice of appropriate thresholds.

In [7], shadow detection is accomplished by combining the probabilities calculated by two separate models: the global bitmap model (GBM) and the strip bitmap model (SBM). The GBM calculated the square root of the weighted sum of square differences between the current image and the reference image. The SBM is a four-step procedure of blob sampling, clustering the samples, matching among clusters, and generating and aging the bitmap model. The weights of the GBM are experimentally found and not explained, other than a note stating that luminosity should be weighted more heavily than hue.

In [8], static shadow detection is performed by maximizing the graph probability using the expectation maximization (EM) algorithm. The algorithm models a single image as a graph with link probability and node probability. Node probability is the probability of a pixel's shadow probability matching the pixel's color information. Link probability is the probability of linked pixels being neighbors. All the link and node probabilities of an image are multiplied together for the final graph probability; however, the link and node probabilities require initialization from shadow and nonshadow pixels before the algorithm can begin execution. The graph probability is iteratively calculated after being initialized until the mean square error is acceptable. The algorithm is not designed to distinguish between moving shadows and static shadows in a video sequence, and the full algorithm is too computationally intensive to perform in a time-critical manner.

In [9], stationary shadow detection is accomplished in a scene where shadows are cast on a flat nontextured surface with uniformly colored objects. Sobel edge detection is executed on the luminance component of the image. The shadow candidate regions are found with horizontal and vertical scanning, whereas morphological processing closes their boundaries. Color edge detection is performed on a normalized color image and goes through the same scanning process to identify object contours. Last, the object contours and the shadow candidate regions are combined to create a cast shadow mask and a self-shadow mask. The assumption of uniformly colored objects on a nontextured surface makes this algorithm unfeasible for traffic scenes with haphazard camera placement and varying environmental conditions.

In [10], shadow removal is required for the effective segmentation of foreground objects. A difference image is generated from the current image and the reference image, and the noise variance is calculated to identify foreground candidates with differences greater than the noise level. A clustering algorithm and a custom color correlation algorithm are applied to these foreground candidates in an effort to find shadows in the scene. Correlation is performed in the hue–saturation–lightness color space between the current image and the reference image; the assumption is that shadow regions will highly correlate with the reference image, whereas foreground objects will have low correlation. The algorithm is computationally intensive and targeted toward identifying shadows in a controlled environment (within a studio). This makes the algorithm ill suited for shadow identification in traffic scenes.

In [11], time and date data are needed to decide if shadow detection is necessary. Unfortunately, the purpose of this paper is to identify shadows attached to vehicles so that sobel edge detection is done to find vehicle contours and shadows that are associated with vehicles. The algorithm cannot be adapted to static shadow detection where stationary objects, which are not necessarily in the image, cast shadows.

In [12], the value ratio between the image and background, and the absolute difference of the image and background's saturation are used to isolate moving shadows. The algorithm requires an empirically determined saturation threshold and a dynamic value ratio threshold. The basic algorithm is useful; however, there are a number of assumptions that are made for dynamic parameter estimation based on the environment that should be reexamined since this paper's algorithm was intended to work both indoors and outdoors.

In [13], EM algorithms and an adaptive Gaussian mixture model were proposed as suitable background generation algorithms that allow pixel categorization as moving shadows. The literature review and testing in [14] show that Gaussian mixture models show little improvement compared to other methods of background generation, making their computational expense unnecessary.

References [6], [15], and [16] present similar algorithms—SAKBOT moving shadow detection through HSV component analysis. One major difference between those papers and this paper is that the absolute difference of hue between the current image and the background image is included in this case. This paper also presents a statistical analysis approach in RGB color space, which uses local, temporal, and spatial information to perform shadow detection. Pixels are given probabilities of membership in three categories—background, foreground, and shadow—and an *a priori* probability is calculated. After pixel classification is complete, scanning and morphological processing form regions. A comparison between the results of the two approaches shows that the statistical approach is best used to distinguish between moving shadows and moving objects, whereas the SAKBOT approach is better for detecting moving shadows. Therefore, the same caveats directed toward [6] apply here as well.

In [17], shadow detection is accomplished by evaluating the three color component ratios for each pixel and categorizing a reference image pixel into foreground, moving shadow, and background classes. A signed singular value decomposition algorithm is used to define the boundaries of the shadow region in the 3-D space with ratios as axes. This paper makes an assumption that RGB ratios are sufficient to identify moving shadows and that a single reference image would be sufficient to categorize shadows at varying times of the day.

In [18], shadows are detected by comparing the two significant components of RGB color space and the two significant components of normalized RGB color space between the background image and the current image. Essentially, the criteria ensure that the shadow pixels darken while maintaining the same color ratios. Morphological processing is done to create shadow regions from the shadow pixels. The criteria used to detect shadows are too lax, and something more restrictive is required.

In [19], shadow detection is performed using an illumination distribution of shadows in a scene. This approach uses the image brightness inside shadows that are cast by objects of known dimensions, where the reflectance properties of the surface are not known in advance. Moving objects are detected and excluded using the spatiotemporal Markov random field model [20]. The background image that is used to generate the illumination distribution of shadows is created using histogram analysis, where the maximum frequency value is used. This algorithm is well suited to the indoor environment; however, it is limited in the outdoor environment because of the unknown lighting conditions.

The work in [21] presents a model-based vehicle tracking system that could be used in shadow detection. In this case, the difference between images is used to perform segmentation. To accomplish motion segmentation, an adaptive background model that models each pixel as a mixture of Gaussian models [22] is used. A dynamic threshold is applied to determine which pixels can be classified as moving objects. This approach uses low-level blob tracking and high-level Kalman filtering. These pixels are then grouped together based on the values of the surrounding pixels.

In [23], an alternate method of shadow detection is proposed. To eliminate characteristics in a scene that will pose confusion for vehicle detection algorithms, background suppression is used. Background suppression includes subtracting the current background estimate from the incoming detector data. Pixel values are then compared with a threshold. If the pixel values are greater than this threshold, they are considered to be a vehicle. This procedure includes continuous updating of the reference background and detection criteria that are continuously adapted to the characteristics of the scene. To compensate for moving shadows, the normal background signature is modified by a gain and/or a bias phenomenon. This algorithm seems rather vague and poorly suited to exclusively detect shadows.

We proposed the use of a shadow detection algorithm that uses background generation and take the difference between the current image and the background image. This difference image will then be normalized according to the maximum value for each color component in the difference image. The normalization will ensure that well-chosen thresholds can be used to detect shadows at varying times of the day. Shadow bitmaps are generated and used to lower the sensitivity of AID systems to incidents in areas of the traffic scene where shadows are detected. This results in fewer false alarms due to shadows.

The proposed method of shadow detection has been fully implemented as a win32 dynamic link library (DLL) module and installed in an AID system running in the TMC in City2. The new AID system with static shadow detection has been tested for a period of three consecutive months onsite with a live video feed. For proof of concept, the same AID system without the DLL shadow detection module was also running for the same period with the same video feed. The results showed that there is a decrease in the number of false alarms due to shadow in the enhanced system with shadow DLL by 96%. The enhanced system with our proposed shadow detection DLL has triggered only 12 false alarms due to static shadows as compared to the same system running without the shadow detection DLL, which triggered 310 false alarms due to shadows.

VI. Snow Detection

Snow presents a serious problem for video-based AID systems. In one example, a vehicle driving through a layer of deep snow left a trail behind on the roadway, which led to false detection by the system (see Fig. 2). In two separate evaluations of all incident detection techniques by Mahmassain *et al.* [24] and Parkany and Xie [25], it was briefly noted that snow (as well as other environmental effects) was a major detriment to using video image processing in incident detection systems. However, no solutions were suggested.

Fig. 7. (Left) Enlarged picture showing the detected corners of vehicles marked by white dots. (Right) Bounding boxes of moving objects and their centers marked by white crosses (original image courtesy of Zang and Klette [27]).

In [26], while dealing with developing an algorithm for diminishing the effects of falling rain, the problem of snow was also recognized. It mentioned that current outdoor vision systems are not able to perform under all weather conditions, be it rain, snow, fog, or mist. It also noted the nature of snow to be dynamic (as opposed to fog, which is largely steady) and described snow's ability for complex trajectories as problematic.

Although there exists widespread acknowledgement that falling snow is a problem in video image processing applications, scant literature research currently exists on the detection of snow on the ground itself.

Removing falling snow from a traffic sequence is detailed by Kamath and Cheung [14]. To do this, they employed spatial and temporal smoothing. To tackle the problem of snow on ground, it is feasible to examine the problem in a different manner. In this respect, several techniques that are not directly related to the detection of snow could be applied, such as popular edge detection, which has been applied to many different problems with similar nature. We propose tackling the detection of snow on the ground that generates false alarms as a problem of trail detection that can benefit from the use of edge detection techniques. A trail can be treated like an object in the scene but with special characteristics; they tend to be narrow and darker than the neighboring road and follow the flow of traffic.

Zang and Klette [27] were able to differentiate objects in the scene by using corner detection and forming boxes around groups of detected pixels using the width and height of each box to differentiate between different objects, specifically segregating cars. This could feasibly be altered to identify snow trails by altering the dimensions of the objects sought. Fig. 7, which was taken from [27], demonstrates their success at identifying different objects in a scene.

Wilson and Dickson [28] described a method to detect road boundaries based on edge detection, which could prove to be useful when applied to the problem of snow trails. In the first step, the boundary of the road is generated by edge detection. In the next step, a demonstration is given on how to find the trajectory of these boundaries through the use of vector algebra inside the windows that are formed by edge points. The resulting vector from this algorithm is demonstrated in a processed video image shown in Fig. 8. Then, a demonstration is presented on how even curved edges can be successfully mapped since vehicles commonly travel in curved trajectories.

The tendency of snow trails toward parallelism (i.e., two sets of tires leave two tracks) could possibly be exploited. In one paper by

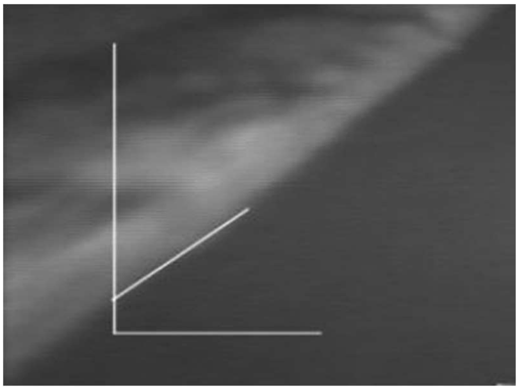


Fig. 8. Border of road with angle detected by algorithm (original image courtesy of Wilson and Dickson [28]).

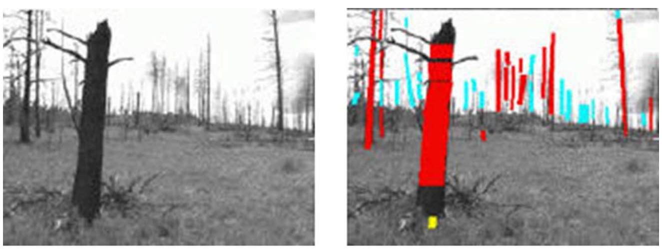


Fig. 9. First example of parallelism that is exploited to remove branches from trunks (original image courtesy of Rankin *et al.* [29]).

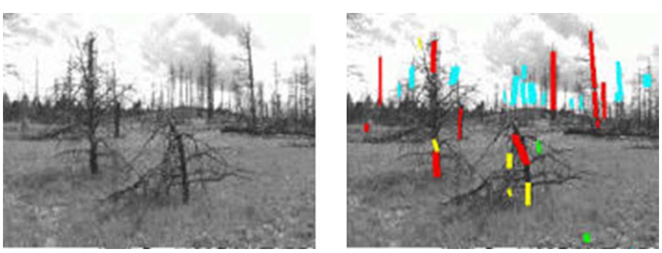


Fig. 10. Second example of parallelism that is exploited to remove branches from trunks (original image courtesy of Rankin *et al.* [29]).

Rankin *et al.* [29], a video processing method for extracting parallel and antiparallel objects from a scene is described. The method described is used in detecting trees in a forested region, taking upright tree trunks and eliminating nonparallel branches. Successful examples of this can be seen in Figs. 9 and 10.

If trail detection were to follow a more traditional edge detection path, then a good scan-line fill algorithm is needed to fill in the gaps once the contours of the trails are detected. One such method is a scan-line fill algorithm such as the one proposed by Hersch [30] to fill the gaps in the edge-detected map. The algorithm proposed in [30] starts by first converting the lines that make up a contour into polysegments with vertices. In the next step, vertical scan conversion creates a pixel for each intersection between scan lines and polysegments. Afterward, the algorithm sets about individually filling each of the internal polysegments. Fig. 11 shows an example of filling a fully joined contour on a pixel map.

In [31], a discussion is presented on the different algorithms for filling contours in raster graphics. Its major feature is the use of the line adjacency graph for the contour to correctly fill nonconvex and multiply connected regions while starting from a "seed pixel," which

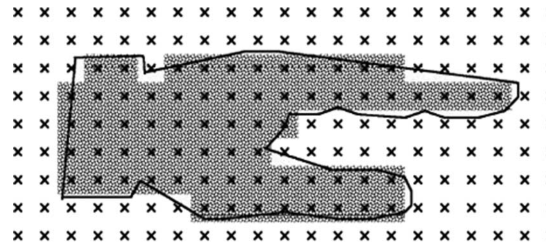


Fig. 11. Example of filling a fully joined contour on a pixel map (original image courtesy of Hersch [30]).

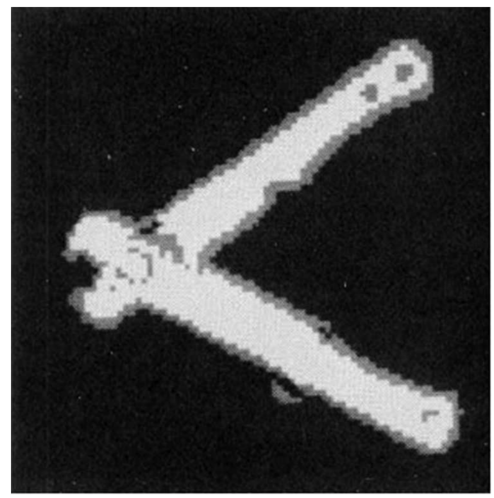


Fig. 12. Example of raster-filled image (original image courtesy of Pavlidis [31]).

is selected according to a separate process. Fig. 12 shows an example result from the algorithm presented in [31]. First, the image of the wire stripper was put through a Sobel edge-detection process. Then, the filling algorithm was deployed, marking the outside of the object as black, the inside as white, and the border as gray.

As it has been seen, the problem of snow, particularly falling snow, is closely linked to another problem—that of rain. Solving these environmental-related issues goes hand in hand.

In [51], the road condition was detected by using image analysis techniques. A multivariate analysis was used to discriminate five kinds of road conditions: "dry," "wet," "slushy," "icy," and "snowy." Features that are related to snow were extracted by texture analysis using the co-occurrence matrix. Snow accumulated on the road can be taken as texture in the image. The feature quantity about coarseness and the directionality of texture were calculated in the road image. The feature of coarseness of texture is extracted as the standard deviation of the gray level in the region of the road. On the other hand, the directionality of texture is extracted as the feature quantity using the co-occurrence matrix. However, this method is suitable for the nonmoving snow. If the snow has been moved, this algorithm will have lower detection accuracy.

We propose the use of a correlation method for snow movement detection. This method has been fully implemented and tested offline on video clips of false alarms that were generated due to snow. The method has been applied to 15 different clips from six different cameras. The method was able to detect the snow movements in all the 15 video clips.

Fig. 13 shows an example of detecting snow movements with our proposed algorithm. It is worth mentioning that this method is currently under deployment as a DLL module to be used for online

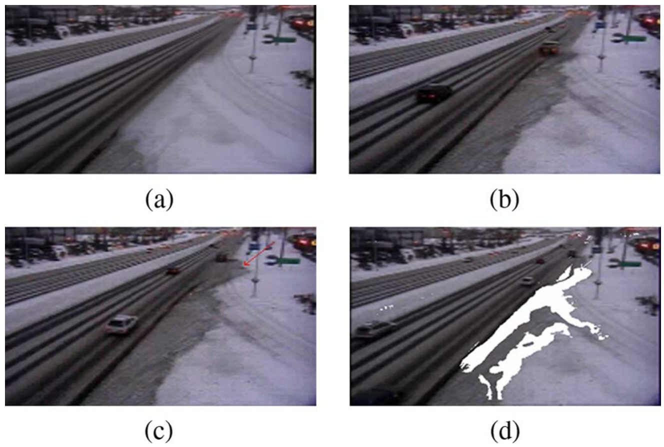


Fig. 13. (a) Original image before a car moves the snow. (b) Image after the car has moved the snow. (c) System without snow detection triggering a false alarm. (d) Enhanced system with snow detection not triggering a false alarm; also, the generated snow map by our snow detection algorithm is superimposed on the image.

testing in the TMC of City2. We expect that the enhancement to the false alarms due to snow movement will be in the 90% range, based on the results that were achieved in offline testing with prerecorded video clips and based on our previous experience with the shadow detection method that was fully implemented and integrated in an actual AID system running in City2 TMC.

VII. Rain Detection

Many of the rain problems arise from rain droplets landing on the dome of the camera itself, blocking the image, whereas water smearing the entire dome of the lens (as might happen in a rainstorm) is an issue without a current foreseeable software solution. Numerous other rain-related issues need to be addressed.

A number of problems arise from a layer of water on the roadway. First, tides of foam washing over the road can set off an incident detection system, as seen in Fig. 3. Also, large puddles can set it off when driven over and splashed around. Last, the wetness of a road causes light to easily reflect, creating lighting and glare problems for the system, which is an issue that is examined on its own in Section VIII.

In [32], standing water, such as puddles, and even larger bodies of water have been characterized and detected by an algorithm developed by Rankin *et al.* The first step is to identify regions by their hue, saturation, and intensity and apply thresholds to segment the scene and obtain possible regions of standing water. After this point, an intensity variance filter is passed over an input grayscale intensity image. This is called low texture detection. Afterward, the image is passed through a spatial filter to smoothen the detection. Next, the image is passed through a reflection detection filter to detect standing water pixels with high amounts of reflection. Note that this step could come in useful when approaching the problem of glare. Ultimately, the results of this long algorithm are able to produce a map of the standing water, which can be seen in Figs. 14 and 15. The different colors denote varying intensities of reflection.

In terms of the actual rain, there have been two algorithms put forward that subtract the rain from the sequence. They employ familiar techniques of spatial and temporal filtering, which have been previously demonstrated in the removal of falling snow from a sequence by Kamath and Cheung [14]. In the method proposed in [26], a correlation model was first produced to capture the dynamics of rain,

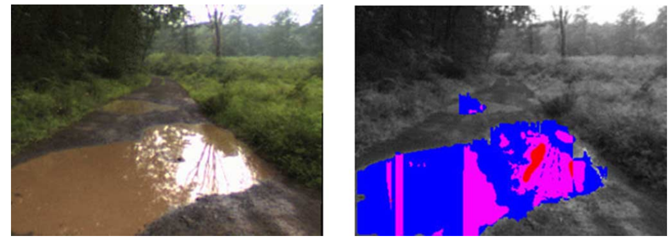


Fig. 14. Puddle on the roadway before and after the standing water detection algorithm is employed (original image courtesy of Rankin *et al.* [32]).

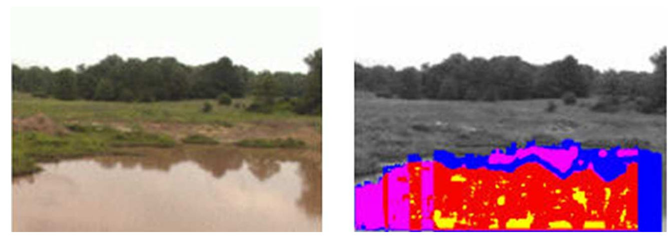


Fig. 15. Placid lake before and after the standing water detection algorithm is employed (original image courtesy of Rankin *et al.* [32]).

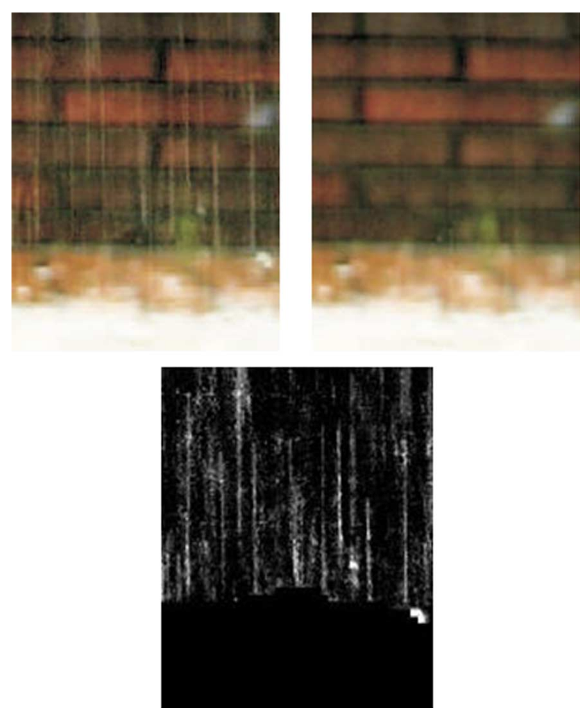


Fig. 16. (Left) Original frame. (Center) De-rained frame. (Right) Removed rain map (original image courtesy of Garg and Nayer [26]).

and then, a physics-based motion blur model was produced to explain the photometry. Applying both of these, algorithms are developed and trained based, in part, on spatial–temporal correlation. An example of the result can be seen in Fig. 16.

Another problem encountered by video-based AID systems is that rain has a tendency to defocus what lies behind it from the camera's perspective. This is evident in Fig. 13; also, this is true when the rain is either on the dome shielding the camera, falling through the air, or on the ground itself. In [33], this defocusing is eased by employing defogging algorithms. Reference [34] presented a solution to the

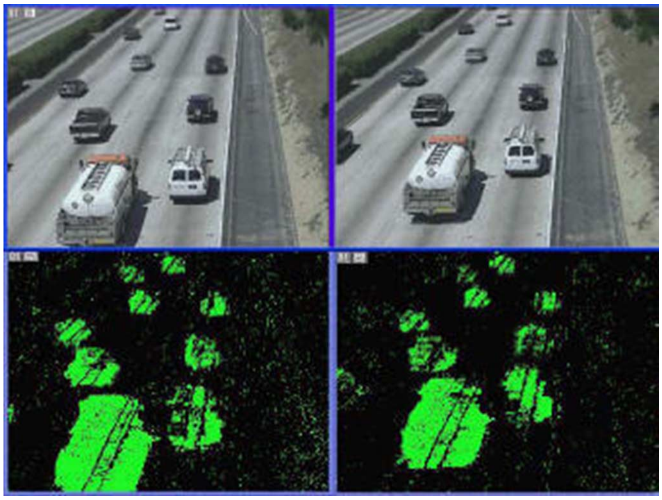


Fig. 17. Two traffic scenes before and after mixture of Gaussians filter is applied (original image courtesy of Zang and Klette [36]).

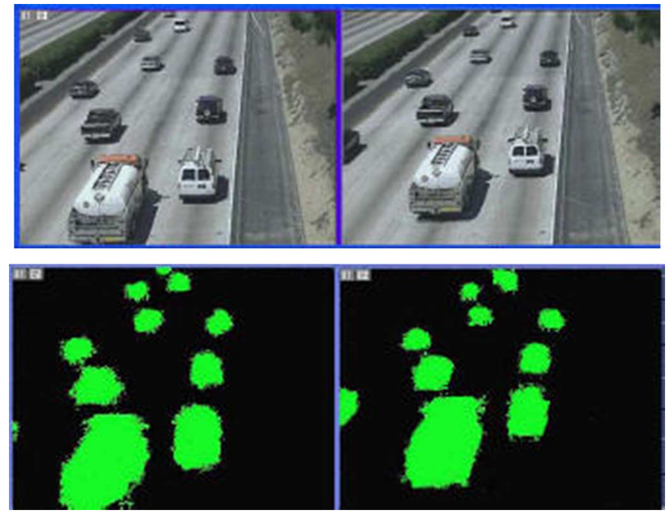


Fig. 18. Two traffic scenes before and after mixture of Gaussians filter and PixelMap are applied (original image courtesy of Zang and Klette [36]).

defocusing problem using automatic focusing algorithms. The work in [34] shows a number of methods to find and restore defocused areas of an image. The simplest method to find a defocused area is to compute a 2-D fast Fourier transform over the area of interest and summing the high-frequency terms, thereby measuring the high-frequency content of the area under question. A well-focused edge transitions from a low-intensity color to a high-intensity color very quickly, whereas a poorly focused edge transitions very slowly. Hence, focused and defocused edges can be located through the use of a sliding window in video image processing terms. The following method to focus the image relies on applying spatial averaging, temporal averaging, edge transition width minimization, and adaptive segmentation. The most important element here is that wherever the edge transition is determined to be too long in comparison to a background reference image, the area can be identified as out of focus, and algorithms are enabled to reverse this.

To remove either falling rain or tides of water on the surface of a road, we proposed a solution based on various forms of background subtraction. This fundamental technique identifies moving objects as portions of the video frame that significantly differ from the background frame. Although very simplistic on its own, combined with other filters, motion detectors, and additional criteria, this could be used to detect the water that is present in the scene by its motion. Several background subtraction algorithms are compared by Cheung and Kamath [35]. The two main methods that were identified in [35] for producing superior results were adaptive median filtering and mixture of Gaussians filtering.

It may be possible to use mixture of Gaussians in aid of detecting rain and moving water in the same way that adaptive median filtering has been used. In [36], it was demonstrated how mixture of Gaussians can be used on a sequence of moving images to construct a background image and, in addition, create a map with moving objects only. Such an example of the moving object map is shown in Fig. 17, with the pixels in motion identified in green.

Note the gaps that appear in the moving vehicles—the mixture of Gaussians algorithm has flaws; however, in [36], the authors went a step further by enacting an additional criterion that they called PixelMap. This added technique identifies differing region levels within an image and accordingly applies different thresholds for mixture of Gaussians. The result of the new criterion has been shown to be more successful, and the improvement is demonstrated in Fig. 18.

A mixture of Gaussians method can be used to detect the rough outline of water foam on the roadway with the PixelMap criterion completing the object highlighting. Rain in midair can be removed with temporal averaging, which benefits from being simple and effective.

These rain or snow detection algorithms are used to create bitmaps that can be used to reduce the sensitivity of AID systems to incidents in areas where snow or rain is detected. This will result in fewer false alarms due to these environmental conditions.

In [51], a method for detecting wet road was proposed. The information about the water on the road can be extracted by calculating the ratio of intensities of the horizontal polarization image to the vertical polarization image taken through the corresponding polarization lenses. The image intensity is high in the place where there is much water on the road in the polarization ratio image. Features that are related to the quantity of water and to the distribution of water are extracted by calculating the mean of the gray levels and the standard deviation of the gray levels in the region of the road. This method may partially be useful for the detection of water foam only when it moves very slowly. However, this algorithm cannot be used to detect water drops on a camera lens, which causes considerable false alarms in AID systems.

VIII. Glare Detection

Glare is also a significant problem that generates many false alarms in video-based AID systems. Glare can be cast by different reflective sources. Wet roads, puddles, road signs, and others are all candidates for casting glare. In the example shown in Fig. 4, turning on streetlights in the evening with a wet road underneath caused an instance of false incident detection. In another case, at nighttime, a car with headlights on drove past a shadow, temporarily lighting it up, causing false detection once the car had past and the glare became extinguished. In another example, a car traveling down the highway at night had some of its headlights reflected onto the road, causing a circle of glare to set off the alarm.

To define the effects of glare more clearly, sources of light cause saturation of the pixel intensities in certain image regions inside which all information about the scene is lost. The central completely saturated part of each image region that is affected by glare is called a primary glare region. In addition to this primary region, there is a circumscribing area that is appreciably affected by the effects of glare but on which intensities are not completely saturated.

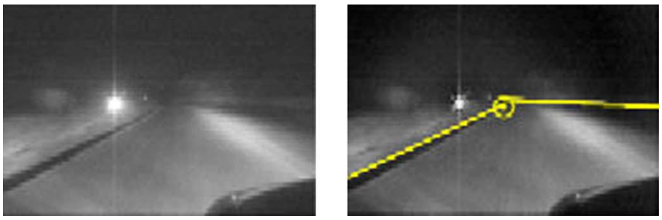


Fig. 19. Two traffic scenes before and after glare reduction is applied (original image courtesy of Andrade *et al.* [40]).

Reference [37] used an algorithm to remove specular reflection from the moving images that were being monitored: in their case, swimmers in a pool. The algorithm proposed in [37] first applied a standard median filtering algorithm to generate a background image and then employed a Markov random field to reduce the amount of specular reflection caused by the water surface. The Markov random fields [38] that were used were essentially a 1-D discrete-time Markov chain.

The research presented in [39] made use of the idea that glare has certain specular properties that could possibly be detected in a hue–saturation–intensity color scheme, where pixels with glare usually have abnormally high saturation and intensity values under the hue–saturation–intensity color scheme, which could lead to their detection and elimination.

In [39], a background subtraction technique was employed together with a general-purpose method for moving visual object segregation.

An entirely different way to approach the glare problem is explored in [40] on a nighttime navigation system for automated vehicles. According to [40], primary glare regions can be identified simply by thresholding the image at a near-saturation intensity level, and then by detecting the contours of all connected components that are formed by the high-intensity pixels. A radius of the region is then detected, and the average intensity is computed within that region. This is used in tandem with interpolated glare intensity to reduce the intensity of the secondary glare region surrounding the focal point. Note that this method does not use precomputed background images for subtraction, which is compatible with the real-time operation. An example of this algorithm in operation is shown in Fig. 19, where the yellow line is used by the authors to denote a specific edge-detected contour.

We propose a solution for detecting glares by performing an edge detection. The use of edge detection detects the outlines of objects in the scene, such as vehicles, road borders, and shadows. Next, the glare detection is performed, which compares neighboring pixels to detect sudden increases in R, G, and B, while maintaining a similar background texture. Then, this is to be filled afterward with a common scan-line algorithm (reference for a scan-line algorithm).

Another possible solution that can be used is to employ background subtraction. Glare tends toward raising the saturation and the intensity of pixels it covers in comparison to those same pixels in a background image. In other words, a background image without glare would be less difficult to compare and subtract a later image with glare spots. Again, to generate a reliable background, any type of an adaptive median filtering [41] or a mixture of Gaussian [42] method may be applied to an initial series of frames from a video. These algorithms will be used to produce glare bitmaps that lower the sensitivity of AID systems in the highlighted areas where glare is present. This will lower false alarms that occur in areas of the traffic scene where glare is detected.

This latter method has been fully implemented and tested offline on video clips of false alarms that were generated due to glare. The method has been applied to 16 different clips from six different cameras. The method was able to detect static glare in all the 16 video clips.

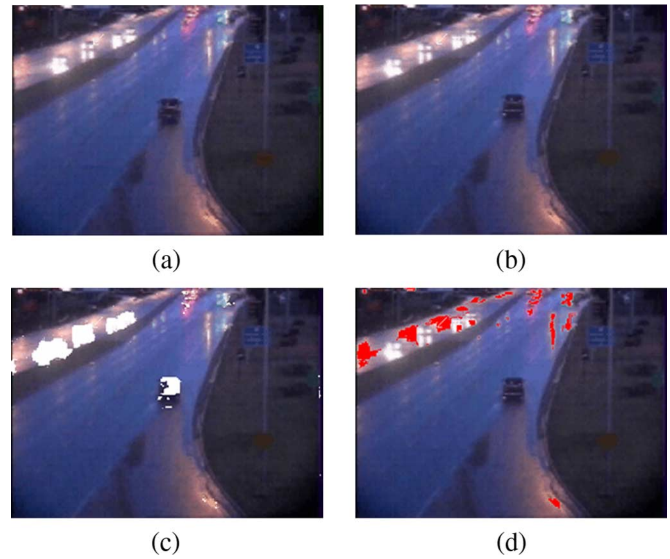


Fig. 20. (a) Original previous color image. (b) Original current color image. (c) Refined motion detection image. (d) Final glare map.

It is worth mentioning that this method is currently under deployment as a DLL module to be used for online testing in the TMC in City2. We expect that the enhancement to the false alarms due to glare will be in the 90% range based on the results that were achieved in offline testing with prerecorded video clips and based on our previous experience with the shadow detection method that was fully implemented and integrated in an actual AID system running in City2 TMC. Fig. 20 shows an example of the detected glare using the proposed glare detection algorithm.

IX. Future Research Areas

As sunlight or moonlight penetrates the atmosphere, it can be reflected, refracted, absorbed, scattered, or diffracted by atmospheric particles or air molecules. The visual effects resulting from this manipulation of light rays are referred to as atmospheric optics.

There has been an effort to incorporate atmospheric optics into ITS. One such attempt has been to examine the natural edges within an image and then compare them with a historical composite image [43]. In this manner, the visibility of the camera can be approximated by determining which edges are visible. Unfortunately, this method is only effective in estimating directional visibility and not useful for extracting specific weather conditions such as snow, rain, glare, or shadows.

Other approaches use hyperspectral imaging (HSI) technology [44]. The use of HSI technology entails using the energy emitted from an object that is collected by a space-based, airborne, or ground-based sensor to identify objects in a scene. The electromagnetic waves that are used to reconstruct an image of an object are subject to the effects of the atmosphere. However, HSI technology does not seem applicable to extracting specific weather conditions. In addition, the use of HSI technology requires spectral signature database usage, subpixel mixing retrieval techniques, scene generation models, and other spectral models.

Currently, stereovision has been widely discussed and is more and more used. Stereovision has the advantage that it is able to obtain an accurate and detailed 3-D representation of the environment around a vehicle. It can produce a complete 3-D view of the traffic scene, which can provide more analysis capabilities for better detection of outdoor environmental factors.

Multicamera systems that were proposed in [52] can be used to reduce false alarms in AID systems. The aim of using multicamera systems is to remove the classic monocular ambiguities and to retrieve the objects' height. The application of the multicameras needs that the AID system has 3-D image processing capability, and the computational time may also be more than expected in regular 2-D detection modules.

Stereovision was also used in [53] to detect the road obstacles either on flat or nonflat road geometry. The detection process is based on the construction and processing of the "v-disparity" image, i.e., the histogram of disparity values for each image line. This image provides a 2-D summary of all the information that is required to detect and estimate the position of obstacles. Furthermore, it provides semiglobal matching and reveals the matches that are the most coherent globally in the 3-D road scene. It allows the estimation of road geometry and obstacle distance.

In [54], a stereovision-based algorithm that is aimed at the detection of pedestrians in infrared images was proposed. The algorithm is based on three different approaches: the detection of warm areas, the detection of vertical edges, and a v-disparity computation. A stereo is used for computing the distance and the size of detected objects.

Based on the discussion presented above, we see stereovision as a promising future direction in the area of detecting environmental conditions and, hence, of enhancing the performance of AID systems. However, as 3-D image processing may require more processing capability and computational time, therefore, the processing time and the detection speed should be carefully estimated before using this method.

A future direction for research may also include investigating the use of atmospheric optics to detect general weather conditions (snow, sleet, rain, etc.) or as a means of object detection via HSI technology. However, at this time, atmospheric optics appears to be an emerging area with many unsolved problems.

Another path of future research may include simultaneous application of the detection algorithms to different weather conditions. The performance of these algorithms is unknown when concurrently applied. Thus, an investigation into the performance of all of these algorithms simultaneously applied would provide insight into the usefulness of these algorithms in a cooperative situation and possible future research problems.

X. Summary and Conclusion

This paper surveys the current state-of-the-art research concerned with shadow, snow, rain, and glare detection. It was proposed that shadow detection can be accomplished by generating a background image, creating a difference image between the background and current images, normalizing the difference image with respect to its maximum color components, and applying thresholds for each color component. Methods in HSV and normalized color space were investigated; however, they require thresholds that are dependent on the time of the day and the angle of the sun.

There are no snow detection algorithms in the literature; therefore, it was necessary to adapt analogous techniques to our own purposes. Snow detection is done by searching for snow trails with edge detection using a scan-line algorithm to bound the region and search for parallel trails.

Rain detection is subdivided into midair rain and rain-on-road detection; however, the literature only exists for midair rain detection. Midair rain can be detected with a temporal averaging algorithm. Rain on the road requires advanced background generation techniques such as adaptive median filtering or mixture of Gaussians. Morphological processing is used to improve the definition of rain foam regions.

Last, glare detection is a heavily researched area. Edge detection between regions containing great differences serves as an effective method for glare detection.

In conclusion, the survey reviewed a number of possible solutions for the problems that cripple AID systems today. This survey also presented the most promising avenues that deserve more research.

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A Misapplication of the Local Ramp Metering Strategy ALINEA

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***Abstract*—In a recent series of articles with largely identical contents and results, some claims are raised about the pertinence and performance of the well-known and widely field-applied local ramp metering algorithm ALINEA and of some extended versions thereof. The expressed claims are based on simulation results with a self-made microscopic simulator. This paper shows that the produced simulation results and derived conclusions are based on an insufficient understanding of the feedback character of the ALINEA algorithm, which led to an inappropriate application of the method. More specifically, the mainstream measurement that feeds ALINEA was misplaced so that any occurring congestion could not be monitored; this renders ALINEA blind to the traffic conditions under control and negates the very notion of feedback.**

***Index Terms*—ALINEA, feedback traffic control, ramp metering.**

I. Introduction

In a recent series of articles [1]–[8] with largely identical contents and results, Kerner raises some claims about the pertinence and performance of the well-known and widely field-applied local ramp

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