Proceedings of the 2007 IEEE
Intelligent Transportation Systems Conference
Seattle, WA, USA, Sept. 30 - Oct. 3, 2007

An Algorithm to Compensate for Road Illumination Changes for AID Systems

Jun Cai[1,2] **Mohamed Shehata** [3,2] **Wael Badawy** [1,2] **Muzamil Pervez** [1]

[1]*Department of Electrical and Computer Engineering, University of Calgary, 2500 University Drive, N.W., Calgary, Alberta, Canada T2N 1N4*
[2]*Smart Camera Technologies Inc., #5, 3535 Research Road, N.W., Calgary, Alberta, Canada T2L 2K8*
[3]*Deptartment of Electrical and Computer Engineering, Benha University, 108 Shoubra Street, Cairo, Egypt*

caij@ucalgary.ca; msshehat@ucalgary.ca; badawy@ucalgary.ca; mspervez@alumni.ucalgary.ca;

Abstract— **Many ITS systems suffer from high false alarm rates due to static glare. Static glare appears in video scenes when the road is wet and light originating from static light source, such as road lamp, is reflected on the road. Often an Automatic Incidents Detection (AID) system will detect occurrences of static glare as incidents, causing the generation of false alarms. In this paper, an effective real-time algorithm is proposed to detect static glare. This algorithm generates a static glare map that can be used by an AID system to avoid static glare false alarms.**

Index Terms— **Static Glare Detection, Automatic Incident Detection (AID), Intelligent Transportation Systems (ITS)**

I. INTRODUCTION

Intelligent Transportation Systems (ITS) is an emerged area to solve the problem of congestion in modern crowded cities. ITS aims at enhancing the efficiency of existing infrastructure in a more cost effective manner than major upgrades to a road network. ITS can be defined as “those systems utilizing synergistic technologies and systems engineering concepts to develop and improve transportation systems of all kinds” [1].

ITS [2] [3] [37] are designed to advocate transport safety. A primary application of ITS is video-based Automatic Incident Detection (AID) which involves processing videos and images from existing cameras mounted along city streets and highways. The AID system is able to detect any traffic abnormalities on a given section of road. Examples of such abnormalities would include vehicles stopping where not instructed to, vehicles reversing or driving opposite to the direction of traffic flow, vehicles dropping cargo on the road surface and vehicles involved in any sort of collision. Systems that can detect these incidents can be useful in alerting authorities in an expedient manner. However, the problem with many AID systems is that the accuracy of detection is reduced by the existence of external outdoor environmental factors. The authors have performed a huge analysis on the different types of these outdoor factors [37] and they concluded that there are main 4 major factors: the presence of static shadows [6] and [31], static glare, snow movement [39] or rain [32-34].

In ITSC 2006, we presented a paper that addressed the problem of static shadow detection [38]. This paper continues on the work of addressing outdoor environmental challenges that affects the reliability of AID systems. In this paper, we will focus on the problem of static glare. When the road is wet and road lamps are on, the road will reflect light from these road lamps or a vehicle’s headlights. The headlights of a vehicle will move with the vehicle. Therefore the glare caused by the moving headlights will also move with the vehicle which is called moving glare. The moving glare usually does not cause false alarms as they do not present a situation similar to a stopped vehicle. However, the road lamps (as an example) are motionless and the glare caused by them is called static glare. In traffic monitoring systems, as static glare appears on the wet road, the system often detects this static glare mistakenly as incidents.

In [4], D. Coltuc et al. explains that pixels with glare have abnormally high saturation and intensity values under the HSI colour schema, which could lead to their detection and elimination. Another way to approach the glare problem is explored in [5] by L. Andrade et al. According to [5], primary glare regions can be identified simply by applying a threshold to the image at a near-saturation intensity level and then detecting the contours of all connected components.

The work presented in [40] used an algorithm to remove reflection from moving images that were being monitored, in their case, swimmers in a pool. The algorithm first applied a standard median filtering algorithm to generate a background image, then employed a Markov random field to reduce the amount of reflection caused by the water surface.

The work presented in [41] made use of the idea that glare has certain properties that could possibly be detected in an HSI colour scheme where pixels with glare usually have abnormally high saturation and intensity values which could lead to their detection and elimination. In this work, a background subtraction technique was employed with a general purpose method for moving visual object (MVO) segregation. However all of these glare detection algorithms mentioned above are not suitable for real-time traffic video application because they are either time-consuming or they only used still images to test their algorithms.

In this paper, an effective real-time approach to the detection of static glare is proposed. To test the proposed algorithm, it has been applied to real live video streams. The remaining of this paper is structured as follows: Section 2 presents an overview of the static glare problem. Section 3 presents the proposed algorithm for static glare detection. In Section 4, experimental results, performance analysis and evaluation are presented. Section 5 draws the conclusions of the paper.

II. THE PROBLEM OF STATIC GLARE IN AID SYSTEMS

In 2005, a project was initiated between Transport Canada, Alberta Infrastructure and Transportation, the City of Calgary, and the University of Calgary to enhance the reliability of AID systems and reduce the amount of false alarms that are produced due to outdoor environmental factors. The authors of this work have developed a novel algorithm for identifying static shadows on roads and use the static shadow maps generated by the algorithm to reduce the number of false alarms triggered by an AID system. The proposed algorithm for static shadow detection was presented in ITSC 2006 that was held in Toronto Canada [38]. After that, the presented static shadow detection algorithm has undergone an online continuous testing for a period of 3 months to integrate it as part of the current AID systems in the Traffic Management Centre (TMC). The obtained results showed that the static shadow detection algorithm was able to reduce the amount of false alarms due to static shadows by 96%. In this paper, we continue on enhancing the reliability of AID systems by targeting another source of false alarms which is static glare.

In a real-time traffic monitoring system, static glare can cause problems. The AID system operates based on the idea that as long as traffic flow is normal there are no alerts, but if something out of the ordinary happens, e.g. a vehicle pulls onto the shoulder or stops in a line or there is a real collision, then the AID system triggers an alarm. Figure 1 shows an image sequence, where the static glare from road lamps begins to appear on the road. The system identifies this static glare as moving object and once it reaches its steady state the system detects it as an incident and generates an alarm. In this example in Figure 1, the static glare is very pale at beginning and then becomes brighter in the images rapidly as the rain continues and more illumination is reflected from the road. The AID system sees this static glare as a moving object and once it reaches its final steady state, the AID generates an alarm.

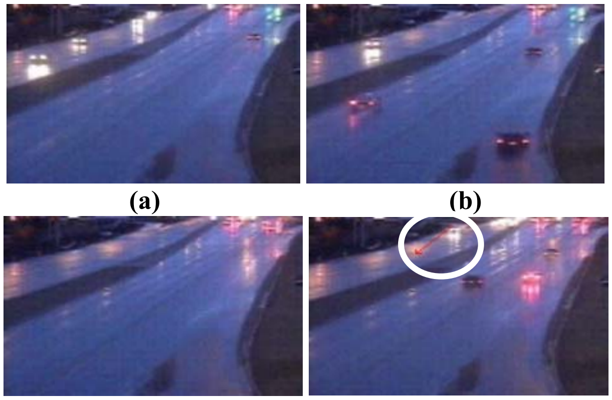

Figure 1: False alarm due to static glare

III. THE PROPOSED ALGORITHM

In the proposed static glare detection algorithm, there are four processing stages, namely: background generation, background differencing, static glare detection criteria application, and static glare map generation. An overview of the static glare detection algorithm is shown in Figure 2.

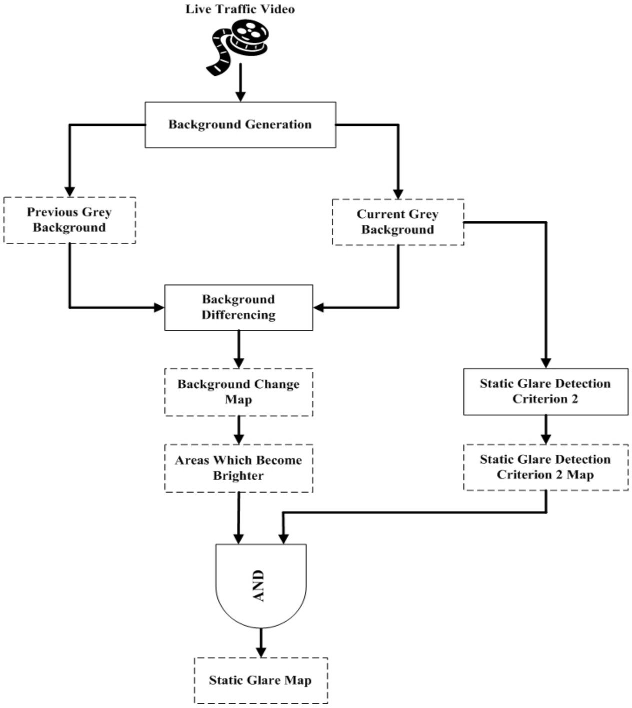

Figure 2: Static Glare Detection Algorithm

A. Background Generation

Background images are generated to eliminate moving vehicles and to obtain a clean image that contains no moving vehicles. Background images can help identify changes due to the appearance of static glare. A median filter is used in the generation of the background images.

The pixels from every third frame of the video are stored in separate buffers for each RGB value at each pixel location. The colour components for each pixel location in the background are calculated as the median of each colour component's pixel location buffer. Equation 1 demonstrates the calculation of a single colour component at a pixel location *x, y* in the median background image, provided that the buffers are sorted monotonically.

$$BI(x,y,CC)=\left\{\begin{array}{ll} Buffer_{x,y,CC}\left(\frac{n}{2}\right) & n \text{ is even} \\ Buffer_{x,y,CC}\left(\frac{n+1}{2}\right) & n \text{ is odd} \end{array}\right\} \qquad (1)$$

Where *CC* is the desired colour component (either red, green, or blue), *n* is the length of the buffer, and *Buffer* is a buffer containing the history of colour component *CC* at pixel location *x, y*. The default setting for the module is to add an image to the median filter on every third frame using *n*=10 as the length of the buffer, resulting in a new background image after 30 frames of processing.

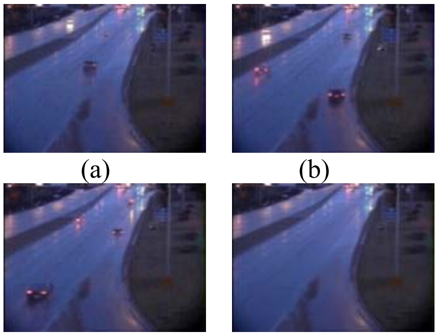
(a) (b)
(c) (d)

Figure 3: Background Generation for Static Glare

B. Background Differencing

The current AID systems always generate false alarms due to static glare when it starts to appear and become brighter, but not when it starts to disappear. So background differencing is performed for background images and two consecutive background images are compared. An overview of the module is presented in Figure 4.

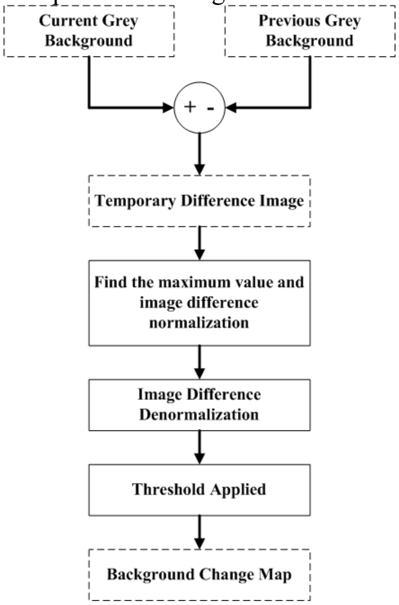

Figure 4: Background Differencing

The temporary difference image is created and can be normalized with respect to the greatest change in the scene. Then a threshold is applied and a background change map is produced. The current grey background is subtracted by the previous grey background to create a temporary difference image (*TDI*) (as shown in Equation 2) to find the area that becomes brighter between the current and previous background images

$$TDI(x,y) = CGB(x,y) - PGB(x,y) \tag{2}$$

Where *CGB* is the Current Grey Background, *PGB* is the Previous Grey Background.

Next, *TDI* is normalized with respect to the greatest difference. To do this, the maximum difference in the *TDI* is first determined to facilitate normalization as follows (Equation 3):

$$maxdiff = \max(\forall_{x,y} TDI) \tag{3}$$

Where $\forall_{x,y}$ refers to every pixel location *x, y* in the *TDI*, max is a function that finds the maximum value in the set, and $maxdiff$ is the maximum difference.

The normalized value in $TDI\_normalized$ is the difference divided by the maximum difference, $maxdiff$, then multiplied by $2^n - 1$ (*n*=8 bits in this project). This facilitates the selection of robust thresholds to define the range of changes to the background, as shown in Equation 4.

$$TDI\_normalized(x,y) = \frac{TDI(x,y)}{\max diff} \times 255 \tag{4}$$

To generate the background change map (*BCM*), the background change map is analyzed using a *threshold* (as shown in Equation 5). This range has been determined empirically and has been found to be consistent through all the different test videos.

$$BCM(x,y) = \begin{cases} 1 & TDI\_normalized(x,y) \geq threshold \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

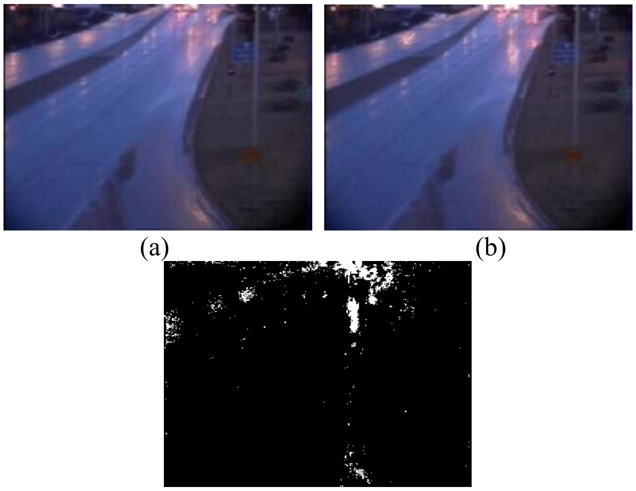
(a) (b)
(c)

Figure 5: Background Differencing (a) previous background image (frames 151-180); (b) current background image (from frame 181-210); (c) background change map

C. Static Glare Detection Criteria

Static glare detection criterion 1 requires that static glare candidate pixels become brighter in the background change maps. Then the static glare detection criterion 2 is used to ensure that the detected areas are bright areas, not the areas that were originally very dark then became brighter.

Static Glare Detection Criterion 1

Pixels that pass this criterion are marked 1 in $Areas\_Which\_Become\_Brighter(x,y)$ (as shown in Equation 6).

$$Areas\_Which\_Become\_Brighter(x,y) = \begin{cases} 1 & BCM(x,y) = 1 \\ 0 & otherwise \end{cases} \tag{6}$$

Static Glare Detection Criterion 2

Criterion 2 states that static glare candidate pixel must have a pixel value greater than the average value of the current grey background image since static glare is brighter than the majority of objects in a scene. This static glare detection criterion is applied using Equation 7.

$$Criterion_2(x,y)=\left\{\begin{array}{ll}1 & CGB(x,y)>\dfrac{\sum_{x,y}CGB(x,y)}{M\times N}\\ 0 & \text{otherwise}\end{array}\right\} \tag{7}$$

Where $\sum_{x,y}CGB(x,y)$ is the summation of the grey pixel value of very pixel location of the current grey background. $M\times N$ is the number of pixels in the image.

D. Static Glare Map Generation

The static glare map (*SGM*) is generated by combining two maps: $Areas\_Which\_Become\_Brighter(x,y)$ and $Criterion_2(x,y)$, as shown in Equation 8.

$$SGM(x,y)=Areas\_Which\_Become\_Brighter(x,y)\cap Criterion_2(x,y) \tag{8}$$

IV. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

A. Experimental Results

The proposed static glare detection algorithm was tested on a number of traffic videos from six cameras installed throughout the City of Calgary. Table 1 shows camera video statistics from camera 1 to camera 6.

Table 1: Camera Video Statistics for Static Glare Detection Algorithm

Camera ID	Video Size (pixels)	Video Duration (seconds)	Number of Frames
Camera 1	388×284	159	795
Camera 2	388×284	159	799
Camera 3	388×284	160	800
Camera 4	388×284	162	812
Camera 5	388×284	159	795
Camera 6	388×284	159	795

The static glare maps generated by the proposed algorithm are compared with the areas that triggered false alarms in Figure 6. The images on the left-hand-side of Figure 6 show the areas that triggered false alarms in the AID system and they are marked by a circle. In this circle, there is a white arrow that represents the false alarm that has been triggered by the AID system due to the static glare. The images on the right-hand-side of Figure 6 show the results of applying the proposed glare detection algorithm. The detected static glare is marked as red in the images. It is noticed that all glare areas that have been triggering false alarms are caught by the proposed algorithm and when the algorithm was implemented on top of the AID systems these false alarms are not triggered.

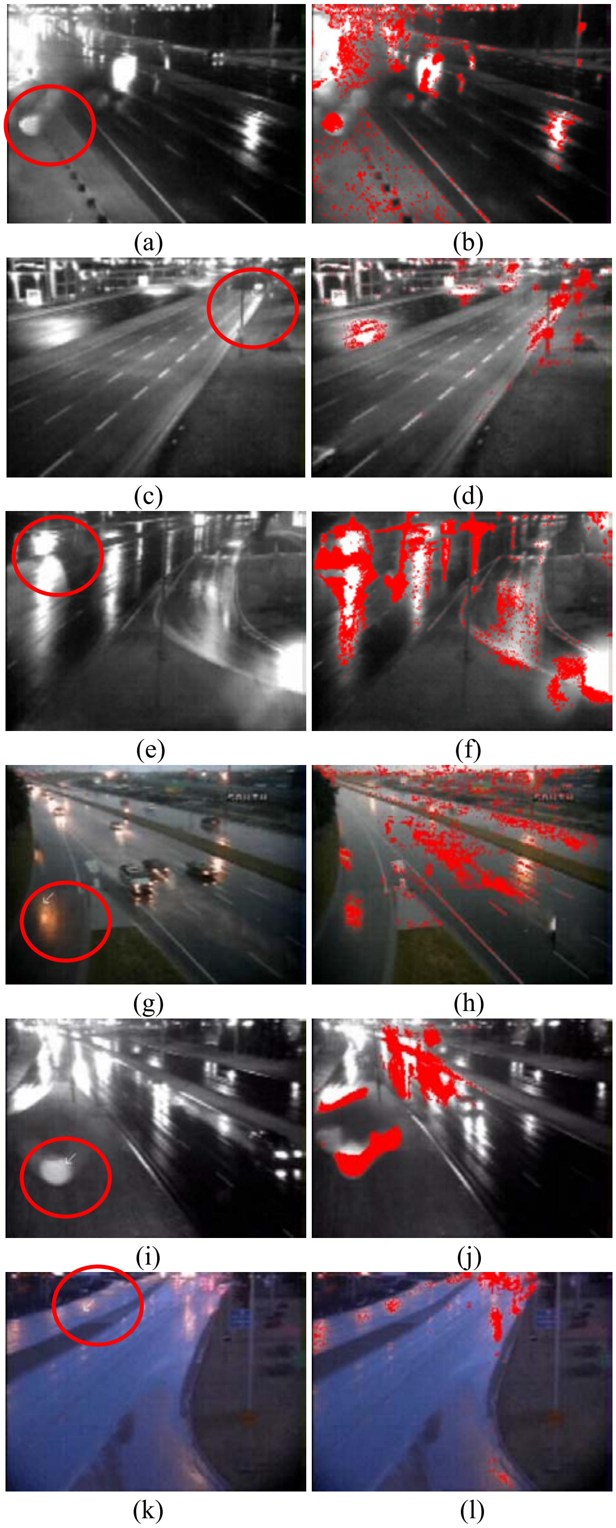
(a) (b)
(c) (d)
(e) (f)
(g) (h)
(i) (j)
(k) (l)

Figure 6: Static Glare Maps from Different Cameras (a), (c), (e), (g), (i), (k) static glare areas that triggered false alarms in six cameras where white arrow inside the circle represents a false alarm; (b), (d), (f), (h), (j), (l) static glare maps generated by proposed algorithm

B. Performance Analysis

Processing times were evaluated to make sure that the proposed algorithm meets the real-time requirement since AID systems' platforms have limited resources.

Table 2: Processing Time

Camera ID	Maximum Processing Time (ms/frame)	Average Processing Time (ms/frame)
Camera 1	15.100000	13.503145
Camera 2	15.633333	13.748436
Camera 3	15.100000	13.632500
Camera 4	15.100000	14.220443
Camera 5	19.266667	13.679245
Camera 6	15.600000	14.230189

Table 2 shows the maximum and average processing time for each frame for generating static glare maps. The videos used to test the algorithm run at 5 frames/second, thus a new frame is generated every 200 ms. The maximum and average processing time are much less than the frame generation speed. So the proposed algorithm can meet the real-time requirement.

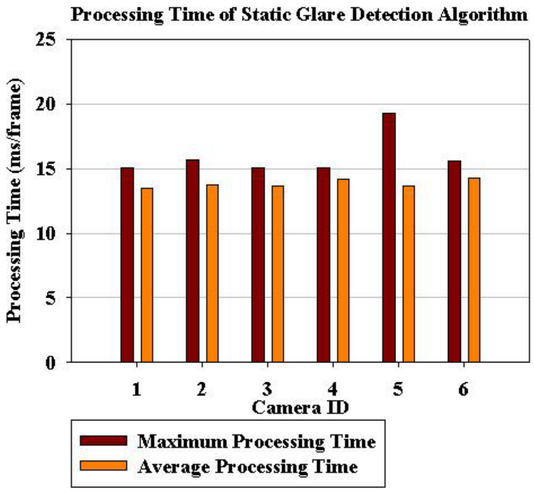

Figure 7: Processing Time of proposed Algorithm

Detection speed was also evaluated to make sure the proposed algorithm meets the real-time requirement. To be eligible for application, the proposed algorithm must have the ability to detect the potential static glare area before AID systems generate false alarms based on those static glare areas so that the proposed algorithm has time to inform AID systems.

For the detection speed, the algorithm can detect the potential static glare area far in advance. The algorithm can inform the AID system in advance by sending the system static glare maps and prevent it from generating false alarms based on static glare as shown in Figure 8. We can see that the proposed algorithm has plenty of time left to inform AID system the static glare maps it generated. This also shows that the proposed algorithm meets the real-time requirement that was previously defined.

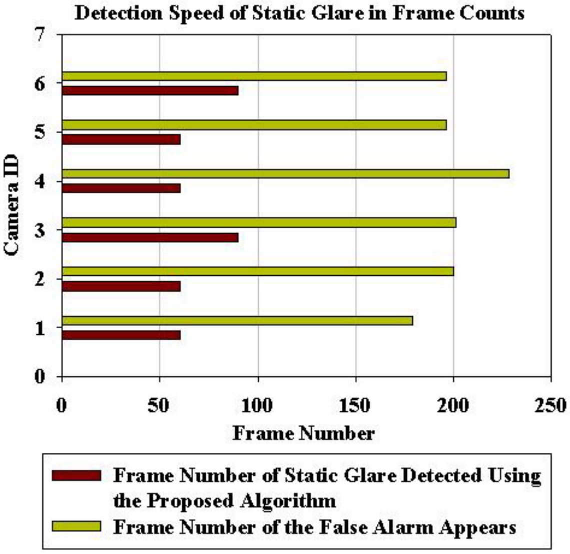

Figure 8: Detection Speed of Static Glare Detection Algorithm

V. CONCLUSION

Static glare is a major cause of false alarms in AID systems. When a static glare begins to appear in the scene, it is treated as an object that has stopped and hence the AID system triggers a false alarm. To address this problem, this paper proposed an efficient real-time algorithm to detect static glare in traffic videos. The method is based on using background images to detect changes. From experimental results, the proposed algorithm successfully detects static glare. Furthermore the processing time and detection speed of the proposed algorithm meet the real-time constraints. With such flexibility, it is intended that such an algorithm could be adapted for use in many different traffic monitoring systems.

ACKNOWLEDGMENT

We would like to thank Transport Canada (Transport Canada has provided co-funding to this project, through Canada's Strategic Highway Infrastructure Program.), Alberta Infrastructure and Transportation, The City of Calgary, Schulich School of Engineering, and the University of Calgary, for their financial and technical support they are providing to us during the period of this project.

REFERENCES

[1] F. Y Wang, C. Herget, D. Zeng "Editorial Developing and Improving Transportation Systems: The Structure and Operation of IEEE Intelligent Transportation Systems Society," *IEEE Transactions on Intelligent Transportation Systems*, vol. 6, issue 3, pp. 261 – 264, Sept. 2005.

[2] Transport Canada, "An Intelligent Transportation Systems (ITS) Plan For Canada: EnRoute To Intelligent Mobility," Technical Report, Nov. 1999.

[3] Transport Canada, "Evaluation of a system for automatically detecting incidents by processing video images from existing cameras monitoring highways," Technical Report, May 13, 2005.

[4] D. Coltuc, P. Bolon, “Color image watermarking in HSI space,” *IEEE International Conference on Image Processing (ICIP 2000)*, vol. 3, pp. 698-701, Sept. 2000.

[5] L.C.G. Andrade, W.F.M. Campos, R. L. Carceroni, “A video-based support system for nighttime navigation in semi-structured environments,” *17th Brazilian Symposium on Computer Graphics and Image Processing 2004*, pp. 178-185, Oct. 2004.

[6] J. M. Scanlan, D. M. Chabries,and R. W. Christiansen,“A Shadow Detection and Removal Algorithm for 2-D Images,” *IEEE International Conference on Acoustics, Speech, and Signal Processing 1990*, pp.2057-2060

[7] J. Yao, Z.F. Zhang, “Systematic static shadow detection,” *Proceedings of the 17th International Conference on Pattern Recognition 2004 (ICPR 2004)*, vol. 2, pp. 76-79, Aug. 2004.

[8] E. Salvador, A. Cavallaro, T. Ebrahimi, “Shadow identification and classification using invariant color models,” *IEEE International Conference on Acoustics, Speech, and Signal Processing 2001 (ICASSP ‘01)*, vol. 3, pp. 1545-1548, May 2001.

[9] D. Grest, J.M. Frahm, R. Koch, “A Color Similarity Measure for Robust Shadow Removal in Real-Time,” *8th International Fall Workshop Vision, Modeling, and Visualization 2003*, pp. 253-260, Nov. 2003, Munich, Germany.

[10] A. Cavallaro, E. Salvador, T. Ebrahimi, “Detecting Shadows in Image Sequences”, *1st European Conference on Visual Media Production (CVMP 2004),* pp.165-174, London (UK), Mar. 15-16, 2004.

[11] A. Prati, I. Mikic, C. Grana and M. M. Trivedi, “Shadow Detection Algorithms for Traffic Flow Analysis: a Comparative Study”, *IEEE International Conference on Intelligent Transportation Systems*, Oakland, California, Aug 2001

[12] P. Kumar, K. Sengupta, A. Lee, “A Comparative Study of Different Color Space for Foreground and Shadow Detection for Traffic Monitoring System”, *The IEEE 5th International Conference on Intelligent Transportation Systems*, Sept. 3-6, 2002, Singapore.

[13] R. Cucchiara, C. Grana, M. Piccardi, A. Prati, “Detecting Moving Objects, Ghosts, and Shadows in Video Streams”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, issue 10, page 1337-1342, Oct. 2003.

[14] E. Salvador, A. Cavallaro, T. Ebrahimi, “Cast shadow segmentation using invariant color features”, *Computer Vision and Image Understanding*, vol. 95, issue 2, pp. 238-259, Aug. 2004.

[15] K. Barnardl and G. Finlayson, “Shadow Identification using Color Ratios”, *Proceedings of the IS&T/SID 8th Color Imaging Conference: Color Science, Systems and Applications*, pp. 97-101, 2000

[16] G.D.Finlayson, S.D. Hordley, M.S.Drew, “Removing Shadows from images using Retinex”, *Tenth Color Imaging Conference: Color Science and Engineering Systems, Technologies, Applications*, Scottsdale, Arizona, Nov. 12, 2002, pp. 73-79.

[17] M. D. Levine, J. Bhattacharyya, “Removing shadows”, *Pattern Recognition Letters* (26) , 2005, pp. 251-265.

[18] R. Cucchiara, C. Grana, M. Piccardi, A. Prati, S. Sirotti “Improving shadow suppression in moving object detection with HSV color information”, *2001 IEEE Intelligent Transportation Systems Conference Proceedings*-Oakland (CA),USA, Aug. 25-29,2001.

[19] A. Yoneyama, C. H.Yeh, C.C.J. Kuo, “Robust traffic event extraction via content understanding for highway surveillance system”, *IEEE International Conference on Multimedia and Expo (ICME)*, Taipei, Taiwan, June 27-30, 2004.

[20] G.S.K. Fung, N.H.C Yung, G.K.H Pang, A.H.S Lai, “Towards detection of moving cast shadows for visual traffic surveillance”, *Proceedings of IEEE International Conference on Systems, Man, and Cybernetics*, vol. 4, pp. 2505-2510, Tucson, Arizona, Oct. 7-10, 2001.

[21] P. L. Rosin, T. Ellis, “Image difference threshold strategies and shadow detection”, *Proceedings of the 1995 British conference on Machine vision*, Birmingham, United Kingdom, vol. 1, pp. 347–356.

[22] O. Stander, R. Mech, J. Ostermann “Detection of Moving Cast Shadows for Object Segmentation,” *IEEE Transactions on Multimedia*, vol.1, issue 1, pp65-76, Mar. 1999.

[23] S. Nadimi, B. Bhanu; “Physical Models for Moving Shadow and Object Detection in Video,” *IEEE Transactions on Pattern Analysis & Machine Intelligence*, vol. 26, no. 8, pp. 1079-1087, August 2004.

[24] I. Mikic, P.C. Cosman, G.T. Kogut, M.M. Trivedi, “Moving shadow and object detection in traffic scenes,” *Proceedings of the 15th International Conference on Pattern Recognition*, vol. 1, pp. 321-324, Sept. 3-7, 2000

[25] S. Tattersall, K. Dawson-Howee, “Adaptive shadow identification through automatic parameter estimation in video sequences”, *Proceedings of the Irish Machine Vision and Image Processing Conference*, Maynooth, Ireland, pp. 57-64, Sept. 3-5, 2003

[26] C.T. Hsieh, E. Lai, Y.K. Wu, C.K. Liang, “Robust, real time people tracking with shadow removal in open environment,” *Proceedings of 5th Asian Control Conference*, July 20-23, 2004

[27] J. M. Wang, Y. C.Chung, C.L.Chang, S.W.Chen. “Shadow Detection and Removal for Traffic Images,” *Proceeding of 2004 IEEE International Conference on Networking, Sensing, and Control*, Taipei, Taiwan, pp. 649-654, Mar. 21-23, 2004

[28] K. Siala, M. Chakchouk, F. Chaieb, O. Besbes, “Moving shadow detection with support vector domain description in the color ratios space”, *Proceedings of the 17th International Conference on Pattern Recognition (ICPR 2004)*, vol. 4, pp. 384–387, Aug. 23-26, 2004

[29] S. Nadimi, B. Bhanu, “Moving shadow detection using a physics-based approach,” *Proceedings of 16th International Conference on Pattern Recognition(ICPR ’02)*, vol. 2, pp. 701-704 , Aug. 11-15, 2002

[30] Y.M. Wu, X.Q. Ye, W.K. Gu, “A Shadow Handler in Traffic Monitoring System,” *IEEE 55th Vehicular Technology Conference (VTC Spring 2002)*, vol. 1, pp. 303-307, May 6-9, 2002

[31] P. Kumar, K. Sengupta, A. Lee, “A comparative study of different color spaces for foreground and shadow detection for traffic monitoring system”, *Proceedings of IEEE 5th International Conference on Intelligent Transportation Systems*, pp. 100–105, 2002

[32] A. Rankin, L. Matthies, A. Huertas, “Daytime Water Detection by Fusing Multiple Cues for Autonomous Off-Road Navigation,” *Proceedings of the 24th Army Science Conference*, Orlando, FL, Nov. 2004.

[33] L. Matthies, P. Bellutta, M. McHenry, “Detecting water hazards for autonomous off- road navigation,” *Proceedings of SPIE Symposium on Unmanned Ground Vehicle Technology V*, Orlando, Florida, 2003

[34] K.Garg and S. K. Nayar, “Detection and Removal of Rain from Videos”, *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’04)*, vol. I, pp.528-535, June 2004.

[35] A.M. Tekalp, *Digital Video Processing*, Prentice Hall, 1995.

[36] Y. Wang, J. Ostermann, Y. Q. Zhang, *Video Processing and Communications*, Prentice Hall, 2001.

[37] M. Shehata, W. Badawy, A. Radmanesh, J. Cai, M. Pervez, T. Burr, “Robust Video-based Automatic Incident Detection: Research, Issues, and Opportunities,” *ITS Canada ACGM (Annual Conference and General Meeting) 2006*, Whistler, Ontario, Canada, June 4-6, 2006.

[38] M. Shehata, M. Pervez, T. Burr, J. Cai, W. Badawy, A. Radmanesh, “On Eliminating Static Shadow False Alarms in Automatic Incident Detection Systems”, *The 9th International IEEE Conference on Intelligent Transportation Systems* (*IEEE ITSC 2006*), pp.759-764, September 17-20 2006, Toronto, Canada.

[39] J. Cai, M. Pervez, M. Shehata, R. Johannesson, W. Badawy, A. Radmanesh, “On The Identification of Snow Movements on Roads,” *IEEE Workshop on Signal Processing Systems (SiPS 2006)*, pp. 360-364, Banff, Alberta, Canada, October 2-4, 2006.

[40] H. L. Eng, K. A. Toh, A. H. Kam, J. Wang, W. Y. Yau, “An automatic drowning detection surveillance system for challenging outdoor pool environments,” *Ninth IEEE International Conference on Computer Vision 2003,* Nice, France, October 13-16, 2003, vol. 1, pp. 532-539.

[41] R. Cucchiara, C. Grana, M. Piccardi, A. Prati, “Detecting objects, shadows and ghosts in video streams by exploiting colour and motion information,” *IEEE 11th International Conference on Image Analysis and Processing 2001*, Palermo, Italy, Sept. 26-28, 2001, pp. 360-365.