

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 7, Special Issue 2, March 2018

Advanced Traffic Signalling System Using Machine Learning

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ABSTRACT: Traffic signals are essential to guarantee safe driving at road intersections. However, they disturb and reduce the traffic fluency due to the queue delay at each traffic flow. In this work, an Intelligent Traffic Light Controlling (ITLC) algorithm. This algorithm considers the real-time traffic characteristics of each traffic flow that intends to cross the road intersection of interest, whilst scheduling the time phases of each traffic light. The introduced algorithm aims at increasing the traffic fluency by decreasing the waiting time of traveling vehicles at the signalized road intersections. Moreover, it aims to increase the number of vehicles crossing the road intersection per second. Firstly, the basic principle of moving object detecting is given by the Background Subtraction algorithm. Then, a self-adaptive background model that can update automatically and timely to adapt to the slow and slight changes of natural environment is detailed. In proposed system I have performed background subtraction for extracting moving object by using (SVM) Support Vector Machine algorithms. The subjects are moving in different angles to the camera plane, on different image scales. This trained SVM is the core of a human detection algorithm which searches optical flow images for human-like motion patterns. A SVM builds a set of hyper planes in a high or multi-dimensional space can be used for regression and classification. High quality of the separation is attained by generating a functional-margin which provides the greatest distance between the nearest training input data points.

KEYWORDS: Intelligent Traffic Light Controlling, signalized road intersections, self-adaptive background, support vector machine, Background subtraction.

I. INTRODUCTION

BACKGROUND subtraction can be defined as a binary segmentation of a video stream, into the foreground, which is unique to a particular moment in time, and the background, which is always present. It is typically used as an interest detector for higher level problems, such as automated surveillance, action recognition, intelligent environments and motion analysis. Dynamic background, where objects such as trees blow in the wind, escalators move and traffic lights change colour. These objects, whilst moving, still belong to the background as they are of no interest to further analysis. Noise, as caused by the image capturing process. It can vary over the image due to photon noise and varying brightness. In some cases, such as low light/thermal, it can dominate. Camouflage, where a foreground object looks very much like the background, e.g., a sniper in a ghilliesuit. Camera shake often exists, a symptom of mount points that are subject to wind or vibrations. This can be considered to be a type of highly correlated global noise. we propose to use a Dirichlet process Gaussian mixture model (DP-GMM) to provide a per-pixel density estimate (DE). This is a non-parametric Bayesian method that automatically estimates the number of mixture components required to model the pixels background colour distribution, e.g., a tree waving backwards and forward in front of the sky will generate single mode pixels at the trunk and in the sky, but two mode pixels in the area where the branches wave, such that the pixels transition between leaf and sky regularly.

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II. LITERATURE REVIEW

[1] A. Elqursh and A. Elgammal, "Online Moving Camera Background Subtraction," Proc. 12th European Conf. Computer Vision (ECCV), 2012

Background subtraction that has been widely used paradigm to detect moving objects in video taken from a static camera and is used for various important applications such as video surveillance, human motion analysis, etc. Various statistical approaches have been proposed for modeling a given scene background. However, there is no theoretical framework for choosing which features to use to model different regions of the scene background. In this paper we introduce a novel framework for feature selection for background modeling and subtraction. A boosting algorithm, namely RealBoost, is used to choose the best combination of features at each pixel. Given the probability estimates from a pool of features calculated by Kernel Density Estimate (KDE) over a certain time period, the algorithm selects the most useful ones to discriminate foreground objects from the scene background. The results show that the proposed framework successfully selects appropriate features for different parts of the image.

[2] O. Barnich and M.V. Droogenbroeck, "ViBE: A Powerful Random Technique to Estimate the Background in Video Sequences," Proc. IEEE Int'l Conf. Acoustics, Speech and Signal Processing, pp. 945-948, 2009.

Background subtraction is a crucial step in many automatic video content analysis applications. While numerous acceptable techniques have been proposed so far for background extraction, there is still a need to produce more efficient algorithms in terms of adaptability to multiple environments, noise resilience, and computation efficiency. In this paper, we present a powerful method for background extraction that improves in accuracy and reduces the computational load. The main innovation concerns the use of a random policy to select values to build a samples-based estimation of the background. To our knowledge, it is the first time that a random aggregation is used in the field of background extraction. In addition we propose a novel policy that propagates information between neighboring pixels of an image. Experiment detailed in this paper show how our method improves on other widely used techniques, and how it outperforms these techniques for noisy images.

[3] H.-Y. Cheng, C.-C.Weng, and Y. Chen, "Vehicle detection in aerial surveillance using dynamic Bayesian networks," IEEE Trans. Image Process., vol. 21, no. 4, pp. 2152–2159, Mar. 2012.

Automatic vehicle detection system for aerial surveillance in this paper. In this system, we escape from the stereotype and existing frameworks of vehicle detection in aerial surveillance, which are either region based or sliding window based. We design a pixelwise classification method for vehicle detection. The novelty lies in the fact that, in spite of performing pixelwise classification, relations among neighboring pixels in a region are preserved in the feature extraction process. We consider features including vehicle colors and local features. For vehicle color extraction, we utilize a color transform to separate vehicle colors and nonvehicle colors effectively. For edge detection, we apply moment preserving to adjust the thresholds of the Canny edge detector automatically, which increases the adaptability and the accuracy for detection in various aerial images. Afterward, a dynamic Bayesian network (DBN) is constructed for the classification purpose. We convert regional local features into quantitative observations that can be referenced when applying pixelwise classification via DBN. Experiments were conducted on a wide variety of aerial videos. The results demonstrate flexibility and good generalization abilities of the proposed method on a challenging data set with aerial surveillance images taken at different heights and under different camera angles.

[4] J. Shi and C. Tomasi, "Good features to track," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Seattle, WA, USA, 1994, pp. 593–600.

No feature-based vision system can work unless good features can be identified and tracked from frame to frame. Although tracking itself is by and large a solved problem, selecting features that can be tracked well and correspond to physical points in the world is still hard. We propose a feature selection criterion that is optimal by construction because it is based on how the tracker works, and a feature monitoring method that can detect occlusions, disocclusions, and features that do not correspond to points in the world. These methods are based on a new tracking algorithm that

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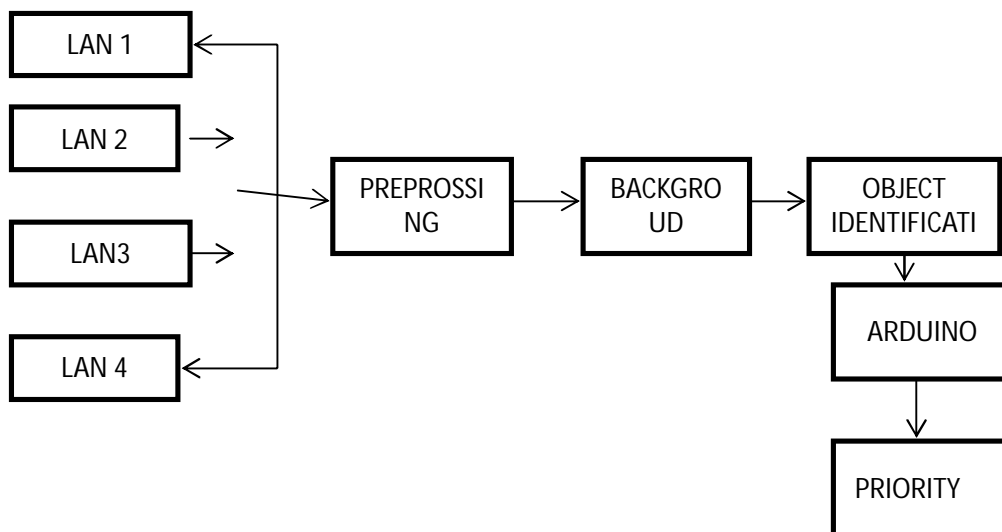
extends previous Newton-Raphson style search methods to work under affine image transformations. We test performance with several simulations and experiments.

[5] X. Cao, C. Wu, P. Yan, and X. Li, "Linear SVM classification using boosting HOG features for vehicle detection in low-altitude airborne videos," in Proc. IEEE Int. Conf. Image Process., Brussels, Belgium, 2011, pp. 2421–2424.

Visual surveillance from low-altitude airborne platforms has been widely addressed in recent years. Moving vehicle detection is an important component of such a system, which is a very challenging task due to illumination variance and scene complexity. Therefore, a boosting Histogram Orientation Gradients (boosting HOG) feature is proposed in this paper. This feature is not sensitive to illumination change and shows better performance in characterizing object shape and appearance. Each of the boosting HOG feature is an output of an adaboost classifier, which is trained using all bins upon a cell in traditional HOG features. All boosting HOG features are combined to establish the final feature vector to train a linear SVM classifier for vehicle classification. Compared with classical approaches, the proposed method achieved better performance in higher detection rate, lower false positive rate and faster detection speed.

III. PROPOSED SYSTEM

Detection of humans in image sequences is an active research area within computer vision. In many applications, such as human-computer interaction, the detection is a basis for tracking. In other, such as surveillance systems or safety systems in cars, the detection in itself is used to trigger some type of alert. Detect patterns of human motion, which to a large extent is independent of the differences in appearance. To achieve this SVM - Support Vector Machine is trained with dense optical flow patterns originating from humans. A SVM builds a set of hyper planes in a high or multi-dimensional space can be used for regression and classification. High quality of the separation is attained by generating a functional-margin which provides the greatest distance between the nearest training input data points. The motion cue used as input to the detection is robustly estimated dense optical flow, where the horizontal flow and the vertical flow between a pair of consecutive images in a sequence. A set of examples of human and non-human flow patterns is collected manually to serve as input to the training.

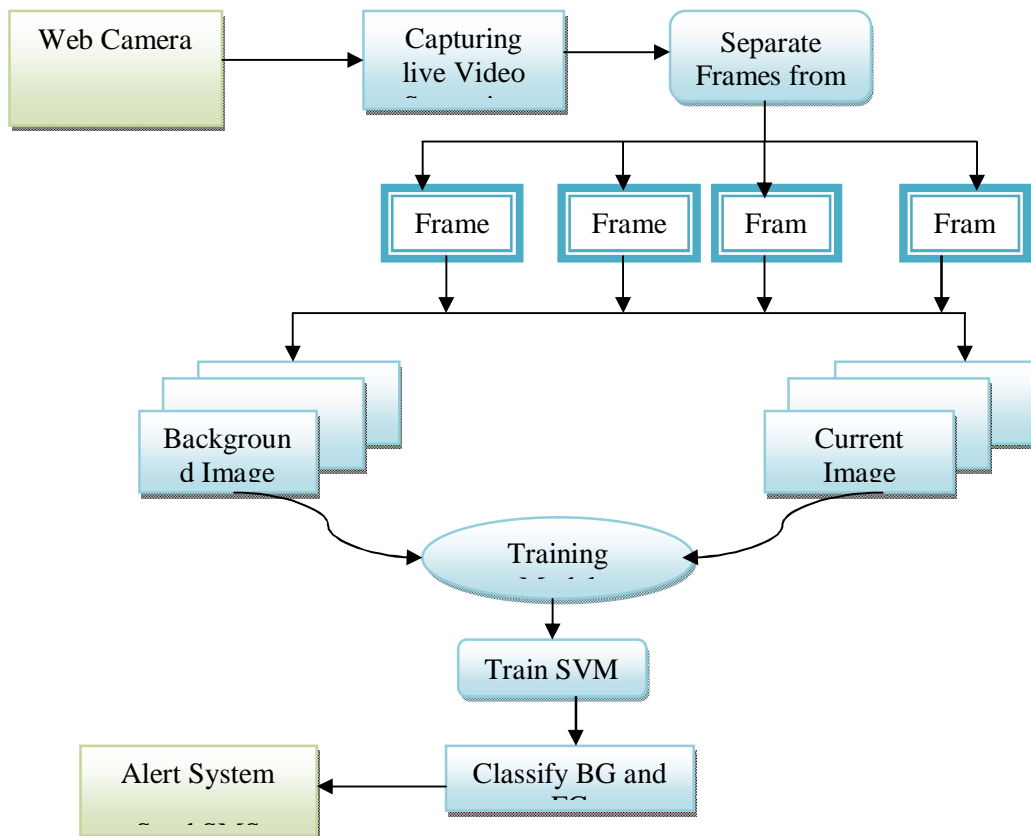


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A. VIDEO TO IMAGE CONVERSION USING PYTHON

In this type the video recording is taken in the form of images like JPG for better ease of access. Python code is used to split the video into images till the recording ends. Here, both the internal camera(0) and the external camera(1) can be used to capture images. The shortcut command “q” is used to exit from the ongoing.

The main objective of converting video recording process. The exit command can also be changed based on the requirements of the user by modifying the code the video into image is the ease of accessibility for an image rather than a video. The main tool used for the conversion of video into images is OPENCV. It converts each frame of a video into image and saves it to the database.

B. TRAFFIC SIGNALLING USING ARDUINO AND LEDs

Based on the analyzed traffic the signalling is done with the help of LEDs and Arduino. The LED’s are used to represent the schematic traffic representation. Based on the previous module input, traffic stimulation can be controlled using LED’S and ARDUINO. The typical traffic signalling system is used to signal the traffic based on the traffic present in that locality.

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C. VEHICLE DETECTION USING OPENCV AND MACHINE LEARNING ALGORITHM

The image captured using python is processed using the opencv tool and the machine learning algorithm (SVM algorithm) is used to analyze the traffic and decide the signal. It can be achieved with the help of background subtraction technique which is subtracts the common region present in both the background and foreground images. The road is always bounded by the Radio Frequency Identification Tag (RFID tag) which is always used to monitor the road. If any traffic rule is disobeyed the RFID tag is used to capture the images of the vehicle or a person.

D. TRAFFIC ANALYSIS

The Machine learning algorithm will analyze the traffic based on the given data sets. this mechanism .

PROPOSED ALGORITHM

Proposed system extends to detect human-like motion patterns instead of appearance patterns, making the detection more robust to difference in appearance due to environment. The proposed method recovers both pose, orientation and position in the image but is computationally heavier. The proposed system was working on the basis of machine learning support vector machine algorithm.



Fig 2.1

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Fig 2.2



Fig 2.3

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Fig 2.4



Fig 2.5

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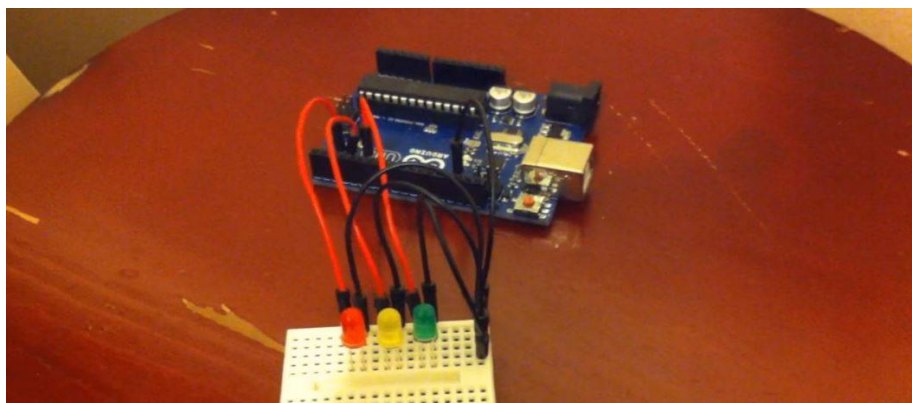


Fig 2.6

IV. CONCLUSION

In this paper, proposed a advanced traffic signalling system using machine learning, To design and implement Cautions System for live video streaming by using Background subtraction technique with SVM algorithm which is useful to provide security where it is necessary. This trained SVM is the core of a human detection algorithm which searches optical flow images for human-like motion patterns. A SVM builds a set of hyper planes in a high or multi-dimensional space can be used for regression and classification. High quality of the separation is attained by generating a functional-margin which provides the greatest distance between the nearest training input data points.

REFERENCES

- [1] A. Elqursh and A. Elgammal, "Online Moving Camera Background Subtraction," Proc. 12th European Conf. Computer Vision (ECCV), 2012.
- [2] R.H. Evangelio, M. PeAztzold, and T. Sikora, "Splitting Gaussians in Mixture Models," Proc. IEEE Ninth Int'l Conf. Advanced Video and Signal-Based Surveillance, pp. 300-305, 2012.
- [3] Y. He, D. Wang, and M. Zhu, "Background Subtraction Based on Nonparametric Bayesian Estimation," Proc. Int. Conf. Digital Image Processing, 2011.
- [4] L. Maddalena and A. Petrosino, "A Fuzzy Spatial Coherence- Based Approach to Background/Foreground Separation for Moving Object Detection," Neural Computing and Applications, vol. 19, no. 2, pp. 179-186, 2010.
- [5] O. Barnich and M.V. Droogenbroeck, "ViBE: A Powerful Random Technique to Estimate the Background in Video Sequences," Proc. IEEE Int'l Conf. Acoustics, Speech and Signal Processing, pp. 945-948, 2009.
- [6] C.C. Loy, T. Xiang, and S. Gong, "Time-Delayed Correlation Analysis for Multi-Camera Activity Understanding," Int'l J. Computer Vision, vol. 90, no. 1, pp. 106-129, 2010.
- [7] A. C. Shastri and R. A. Schowengerdt, "Airborne video registration and traffic-flow parameter estimation," IEEE Trans. Intell. Transp. Syst., vol. 6, no. 4, pp. 391-405, Dec. 2005
- [8] C. Harris and M. J. Stephens, "A combined corner and edge detector," in Proc. 4th Alvey Vis. Conf., 1988, pp. 147-151.
- [9] J. Bouguet, "Pyramidal implementation of the affine lucaskanade feature tracker description of the algorithm," Intel Corp., vol. 5, pp. 1-10, 2001.
- [10] G. Bradski, "The OpenCV Library," Dr. Dobb's Journal of Software Tools, 2000. [35] R. Ke, S. Kim, Z. Li, and Y. Wang, "Motion-vector clustering for traffic
- [12] J. Shi and C. Tomasi, "Good features to track," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Seattle, WA, USA, 1994, pp. 593-600.
- [13] A. Puri, K. Valavanis, and M. Kontitsis, "Generating traffic statistical profiles using unmanned helicopter-based video," in Proc. IEEE Int. Conf. Robot. Autom., Rome, Italy, 2007, pp. 870-876.
- [14] W. Yao, S. Hinz, and U. Stilla, "Automatic vehicle extraction from airborne LiDAR data of urban areas aided by geodesic morphology," Pattern. Recog. Lett., vol. 31, no. 10, pp. 1100-1108, Jul. 2010.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

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- [15] L. Eikvil, L. Aurdal, and H. Koren, "Classification-based vehicle detection in high-resolution satellite images," *ISPRS J. Photogramm. Remote Sens.*, vol. 64, no. 1, pp. 65–72, Jan. 2009.
- [16] Q. Yu and G. Medioni, "Motion pattern interpretation and detection for tracking moving vehicles in airborne video," in *Proc. IEEE Conf. Comput. Vis. Pattern. Recog.*, Miami, FL, USA, 2009, pp. 2671–2678.
- [17] X. Cao, C. Wu, J. Lan, P. Yan, and X. Li, "Vehicle detection and motion analysis in low-altitude airborne video under urban environment," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 21, no. 10, pp. 1522–1533, Jul. 2011
- [18] Y. Lin and S. Saripalli, "Road detection from aerial imagery," in *Proc. IEEE Int. Conf. Robot. Autom.*, Saint Paul, MN, USA, 2012, pp. 3588–3593.
- [19] Z. Kim, "Realtime road detection by learning from one example," in *Proc. IEEE Workshop Appl. Comput. Vis.*, 2005, pp. 455–460.
- [20] R. Pless and D. Jurgens, "Road extraction from motion cues in aerial video," in *Proc. ACM Conf. Geosci. Inf. Syst.*, 2004, pp. 31–38.
- [21] S. Hinz, J. Leitloff, and U. Stilla, "Context-supported vehicle detection in optical satellite images of urban areas," in *Proc. IEEE Int. Conf. Geosci. Remote. Sens. Symp.*, 2005, pp. 2937–2941.
- [22] H.-Y. Cheng, C.-C. Weng, and Y. Chen, "Vehicle detection in aerial surveillance using dynamic Bayesian networks," *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 2152–2159, Mar. 2012.
- [23] X. Cao, C. Wu, P. Yan, and X. Li, "Linear SVM classification using boosting HOG features for vehicle detection in low-altitude airborne videos," in *Proc. IEEE Int. Conf. Image Process.*, Brussels, Belgium, 2011, pp. 2421–2424.
- [24] T. Zhao and R. Nevatia, "Car detection in low resolution aerial images," *Image Vis. Comput.*, vol. 21, no. 8, pp. 693–703, Aug. 2003.
- [25] T. P. Breckon, S. E. Barnes, M. L. Eichner, and K. Wahren, "Autonomous real-time vehicle detection from a medium-level UAV," in *Proc. 24th Int. Unmanned Air Veh. Syst. Conf.*, 2009, pp. 29–37.
- [26] A. Gaszczak, T. P. Breckon, and J. Han, "Real-time people and vehicle detection from UAV imagery," in *Proc. SPIE Elect. Imag. Int. Soc. Opt. Photon.*, 2011, Art. no. 78780B.
- [27] K. Khaled, C. Benjamin, P. Claude, and V. Pascal, "A vision algorithm for dynamic detection of moving vehicles with a UAV," in *Proc. IEEE Int. Conf. Robot. Automat.*, 2005, pp. 1878–1883.
- [28] X. Cao, J. Lan, P. Yan, and X. Li, "Vehicle detection and tracking in airborne videos by multi-motion layer analysis," *Mach. Vis. Appl.*, vol. 23, no. 5, pp. 921–935, Sep. 2012.
- [29] X. Cao, C. Gao, J. Lan, Y. Yuan, and P. Van, "Ego motion guided particle filter for vehicle tracking in airborne videos," *Neurocomputing*, vol. 124, pp. 168–177, Jan. 2014
- [30] H. Yalcin, M. Herbert, R. Collins, and M. J. Black, "A flow-based approach to vehicle detection and background mosaicking in airborne video," in *Proc. IEEE Conf. Comput. Vis. Pattern Recog.*, 2005, p. 1202.