VEHICLE RETRIEVAL USING SIMILARITY MEASURE CHECK FOR OPTIMAL FEATURE SELECTION

Rashmita khilar[1], K.Lalitha[2], S.Sylvia Irish[3]

Associate Professor[1], Assistant Professor[2],[3]

[1,2,3]Department of Information Technology

[1]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences,Tamilnadu, Chennai, India.

[2,3]Panimalar Engineering College
Tamil Nadu, Chennai, India

[1]rashmita.khilar@gmail.com

Abstract

Vehicle retrieval is a demanding application in interdisciplinary research areas such Vision-Based Intelligent Transportation System (ITS), finding traffic density, recognising licence plate, analysing traffic flow etc., Vehicle retrieval becomes possible by detecting and tracking the vehicles. An efficient framework for vehicle detection and tracking system to retrieve vehicle is a great demand in the field of ITS system. In this paper vehicle retrieval based on vehicle detection and tracking is developed based on selecting high level feature set like size and shape for an efficient vehicle retrieval system which is in turn helps to reduce the traffic flow on highways thereby reducing accidents happen on road, autonomous vehicle guidance, vehicle safety, helps in finding the parking slot and identifying suspicious vehicles etc. Mostly vehicle retrieval systems are query based, attribute based such as colour, shape, size etc., and licence plate based retrieval. In this paper vehicles are retrieved from various features like increasing number of vehicle on the road day-by-day, increasing number of cameras etc., Multidirectional Grey-Level Texture and Shape Model for Feature Based Vehicle Retrieval System (MDGLTS -VRS) for vehicle retrieval has been developed. This approach identifies an optimal subset of features, useful to discriminate between local and global features.

Keywords: Vehicle Detection, Retrieval, Multi directional, Multi level, Grey scale, texture, shape, discriminate

1. Introduction

With rapid advances in computer engineering related to the field of designing and managing the database, hundreds of many features are currently handled in the field of data mining and warehousing, Artificial Intelligence, Pattern matching and machine learning. Processing such a large dataset is very complex and it is a very demanding process, since many of the machine learning techniques that are developed till now functions perfectly on small projects (Zexuan et al. 2007). It is identified that the concept of feature selecting many features and working on various features solves enormous problems like eliminating irrelevant features as well as redundant features.

1.1 Feature Selection Approaches

As shown in Figure 1, Feature selection is broadly categorised to 3 different methods: 1) the filter method, 2) wrapper method, and the embedded method. Selecting the type of feature includes features like color, edge, stereo, motion, and texture. A diagrammatic representation of feature selection approaches is given below in Figure:

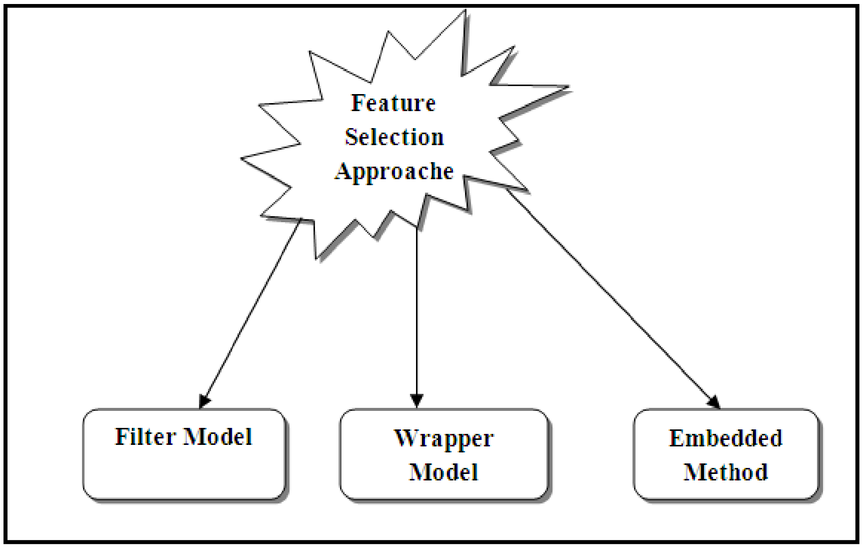


Figure1: Feature Selection Approaches

Methods for selecting feature are broadly categorized into three different types: 1. supervised methods, 2. semi-supervised methods and 3. Unsupervised methods. The label information uses the concept of selecting supervised method effectively which in turn select features from discriminative and relevant features and in turn it is used to distinguish sample features from different many classes. Other supervised methods are also used, but feature selections method which are done using semi supervised one is used to select features for a very small quantity of data. Some of the existing Semi-supervised feature selection algorithms are discussed by Miao & Niu (2016), which are advanced in nature and they mostly rely on a similarity matrix construction and then features that best fit the concept of similarity matrix are chosen. The non appearance of such labels like discriminative features which are unsupervised in nature used for feature selection which are far more difficult method when compared to various other methodologies discussed by many researchers.

The set of features is divided into three different categories based on the various search techniqu es used and implemented, they are 1. Filter, Wrapper and Embedded methods.
The datasets are trained in the filter system, without any learning algorithms being used; on the other hand,

with the aid of any learning algorithm, the wrapper approach used to test the functions directly. T he wrapper model works better than the filter model but is considered more complex in computat ional terms. The filter approach is best and most helpful when high computational efficiency is u sed with a large number of apps. The embedded method is the less expensive when compared to wrapper model. Computational complexities are less, and almost nil prone to errors due to over-fitting.

2. Review of Prior Work

The process for feature selection includes two major steps: 1). Feature extraction and selection. Many features like color, texture and shape information of images have been used to represent objects. A feature that represents an object is termed as object features, which are distinguished as c**olor feature, Texture feature and Shape features**

The texture feature is an essential feature attribute in the field of image processing and vision-based analysis. Texture feature finds its major use in segmentation and also in discriminating distinct objects or regions which is used for classification or recognition system. With large variations with texture content in outdoor environments, it is found that a unified texture model is unavailable. large range of descriptors are suggested to preserve texture in complex environments, and trying to explore a large number of frames include lighting invariant, rational- invariant descriptors and texture strengths like uniform texture area and structural elements, such as probabilistic spatial gray-level.

Several research groups have been established in recent years and they concentrate on the GLCM to develop a finite discrimination of an entity and thus to develop invariant power (elzinis et al 2007) has proposed a method based on GLCM's variance and different level of discrimination over the measurements of distance. The above algorithm is assessed to prove its robustness in an invariant property.

The author Heikkila 2007 et al., enforced a statistical analysis of texture features on the images of iris using different GLCM texture features like mean of the features, variance, contrast of the pixels and second moment of angular moment. Spatial measures on dependencies are based on the angular relationship between neighboring spatial regions and they have angular distances that are measured between the pixels. The above approach of the researchers uses the concept of SVM classifier which is trained with a vector value which has only four values as feature sets. With these reduced feature improvises the size of vector, produces a good classifier and there is an improvisement in the speed which in turn improves the texture classification performance. The author Wei et al. has combined the concept of GLCM and texture features from the co-occurrence of the matrix with edge feature sets which is used for classifying more than 20 different feature types of artificial textures features

Color is a key attribute in image analysis and vision applications, and it is most widely used for image retrieval systems because most of the simple extraction procedure involved are finite discrimination over other images and objects. Moreover, color featurs are insensitive and it is prominent to orientation changes and scale transformations. These color features are calculated from an arbitrarily color space model. The characteristic of similarity of color features mostly depends on the color space model. The Color quantization is a process used in pre- and post-processing of colors due to the usage of large numbers of colors in a single image, and it is used for color feature extraction. This simplifies the the concept of color feature vector and adds salubrity in dealing with color uniformity.

Shape features are generally characterized into either of types like boundary-based or region-based. The shape region of the vehicles is partitioned into simpler forms and also it is represented by a set of primitives, e.g. polygons. It is not that easy while selecting shape feature, various specific characteristics of the application domain have to be considered. Feature analysis and comparisons are performed on it. It is understood concept of estimating the similarity and dis-similarity among the objects which are alike, as suggested by the author Papathomas et al., The above problem is a difficult in order to find the similarity between objects.

The author Agaian et al. Proposed a method for detection of acute myelogenous leukemia from microscopic images. The author have constructed an effective algorithm for selecting best optimal feature, which contains various GLCM texture features like color, shape features etc., The algorithm named complex blood smears is identified using enormous combination sets, and the problems behind the variations is the projections which is then solved later.

In general, collections of things are marked as important, obsolete, or redundant. Therefor e, in the selection procedure of features it is indeed necessary to select possible feature subset from the existing feature sets, without losing any features. Thus optimised feature subsets are obtained which has maximum data accuracy.

For any kind of retrieval system, the process of feature selection is performed in order to select maximum alike features sets and they are considered as the most required features, the above process is carried out by the following possibilities.

- Dimensionality reduction – used for requirement of very low memory and it reduces the cost of computations using machine learning concepts

- Reduction in Feature set – It reduces the feature sets in-order to retain the most relevant sample features.

- Improving Performance - It reduces the computational cost and improves the classification speed of machine learning algorithms.

- Data understanding – It eliminates the occurrences of redundant features based on knowledge on feature selection which generates composite features and the data samples are used for distinguishing different feature sets.

Several approaches, like ICA, PCA and LDA, are proposed to find the most effective feat ure selection and reduction algorithm.

ICA is known as a linear method of transformation that reduces the statistical dependency of features.

The author Janecek et al., identified similarity of features based on reduction techniques of feature set and thereby evaluating the feature subset using Information Gain method and the wrapper- method is used to reduce the dimensionality in the feature subsets, feature extraction technique is also used and they depends on various PCA transformations algorithms. The efficiency in object classification based on feature subset selection is examined on different datasets, It is identified as feature extraction algorithms based on PCA is mostly depend on domain sets where as for classification of objects, features are selected based on wrapper method and it has a high impact on accuracy.

Vehicle retrieval is a demanding process because vehicles appear in any direction, and vary in size, shape and colour. Hence a better feature selection algorithm is required to mitigate the above problem. On the other hand traffic videos are most likely to get affected by various illumination conditions with complex backgrounds. After various study, It is identified that:

- The existing feature selection algorithms depend on various parameters, such that the threshold values are used to analyse and find out the total number of features present in the final data set.
- It is studied that a good algorithm for selecting prominent features is required with less interval of time
- A unique algorithm is required for feature selection and consistent feature samples are taken and tested with finite discrimination.
- Most of the system requires a method or an efficient algorithm which will select relevant features required for the vehicle retrieval system by eliminating irrelevant, unwanted features.

The above mentioned issues based on feature selection algorithm requires the development of new methodology to resolve current issues like selecting optimal features from highly dimensional reduction set of features which is then used to detect presence of vehicle from input traffic videos. The above requirement is usually employed for texture extraction form multiple directional such as at 0^0, 45^0, 90^0, 135^0, 180^0, 225^0, 270^0, and 315^0 is highly demanded, along with shape models. The above methods are carried out, for selecting optimal features at different levles, in order to retrieve vehicles. The above proposed algorithm performs much better than the existing methods. The above algorithm performs much better than other methodologies; the above algorithm is based on the criteria like total number of selected features selected and analysis of error rate.

In this paper, a novel algorithm is designed to solve all the above analysed problems. The algorithm introduces and focuses on decomposing a tracked vehicle taken from traffic videos, feature extraction algorithm is used to extract features from different orientations, and thereby optimal features are selected by using various methods like consistency-based on multi-level feature selection algorithm for retrieving vehicles.

3. FEATURE SELECTION BASED VEHICLE RETRIEVAL SYSTEM

The ability to automatically search for a particular vehicle is extremely useful in an investigative process. To present a complete, automatic system for a vehicle search in outdoor traffic surveillance, highly stable and invariant semantic attributes are required. Existing methodologies like the edge information-based (MaXiaoxu & W. Eric L. Grimson) vehicle classification and 3D model-based approaches (Papageorgiou & Gérard Medioni 2009) are ineffective with low-resolution cameras. In recent years, traffic density has increased, alongside subtle changes in the general appearance of motor vehicles.

Traditional methods Anagnostopoulos et al., of extracting the number plates of vehicles for recognition are unable to keep pace with current trends. So then, to provide a complementary search, the vehicle recognition framework permits vehicle classification to commence, based on attributes such as color, size, length, width and texture In particular, the vehicle retrieval system needs to be robust to challenging outdoor traffic environments and support the demands brought on by time constraints for real-time applications. A powerful similarity measure is required to retrieve the vehicle region.. By using a similarity measure check. A powerful similarity check measures are required for retrieving the vehicle region from traffic videos.

3.1 Vehicle Retrieval using Similarity Measure check

The above proposed selects an optimal set of total of 8 features from a large set of multi-directional texture combined with shape features extracted from vehicle regions as shown in Figure 2. In this paper a methodology is designed for feature selection based on filter method. which increases Euclidean spacing distance, scoring the features, selecting the most relevant features from optimal features with peak distribution, decidedly useful in discriminating between the vehicle objects for vehicle retrieval system. Arrospide et al., combines appearance analysis with motion model and vehicles are classified with help of support vector machines (SVM) using possible inter-dependencies in their trajectories. But descriptor used involves a much larger feature space which is too costly for real-time applications. George et al., extracted frequency concept for calculating coefficients from detected regions. Labelling of vehicles manually is used in Artificial Neural Network (ANN) for auto classification. Due to manual labeling maximum confusion is occurred in case of moderate illumination category which is obvious in outdoor high way traffic monitoring. Here in this work the computation of similarity between two vectors can be replaced by calculating the similarity of texture and shape independently. The formula used to compute similarity is as follows.

S1= G|| Fd . Fu ||

S2= S|| Fd . Fu ||

If S1 >αG || S2 > αS

Assert match:

end

Where, ||.|| represents matching rate.

Fd – data base feature

Fu – unknown feature (Input video)

G||.||- texture similarity measure.

S||.|| - shape similarity measure.

αG, αS – stopping range.

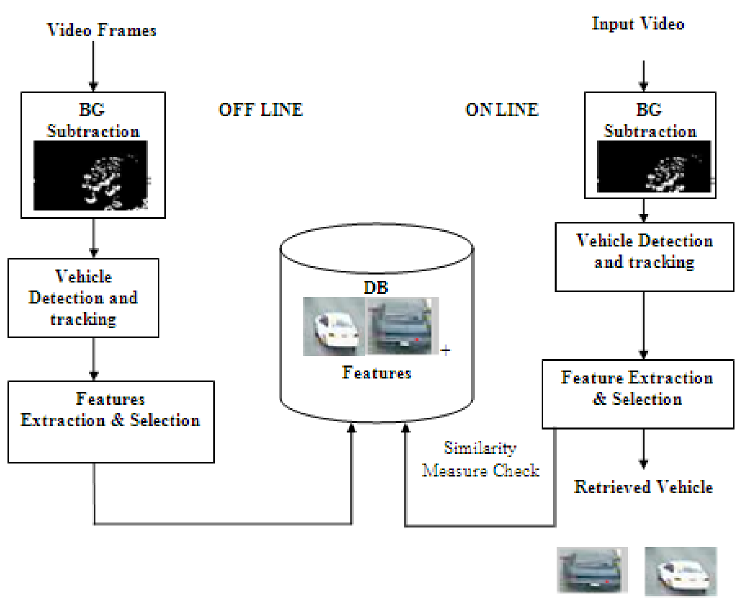


Figure 2: Vehicle retrieval systems

The whole feature samples are weighted through the distance measure method above. Each vehicle image in the database is transformed into a “weighted attribute vocabulary”, along with the index values, so that the similarity between the database images with the query values can be computed with the “ED distance similarity”. The stopping range is formed between two vectors. If the matching rate reaches an optimal degree, it means that the two vectors have a high similarity.

The similarity measure decreases if the attributes vary for the following reasons:

- Vehicles with similar color models offer poor discrimination with the texture descriptor.

- Vehicles in different colors may have a similar appearance and shape and give similarity scores with shape attributes.

4. RESULTS AND PERFORMANCE ANALYSIS

4.1 Experimental Results

A total of 184 features are considered for evaluation and all the features are derived from texture component method and shape features is considered in the proposed method, from the detected vehicle regions in traffic videos from various angles.

The ranking of features are based on their variance and the Euclidean distance spacing algorithm. Based on the above methods the best feature selection and various ranking techniques are identified based on the measures of consistency and correlation coefficient. The subsets are formed in the first level, based on the consistency factors are calculated in all directions. Here, the most accurate and relevant features to the subject classes are selected. The total numbers of features filtered in the first level are 10 from texture and 6 from shape. Thereafter, the correlative natures of the relevant features are measured to eliminate frequently occurred feature samples. Finally, the variance level is measured for scoring the features which are taken, based on their scores in the matching-based vehicle retrieval process. There are totally 22*8 features and 7 shape features. Table 1 shows the total number of features used for feature selection. The 183 features above are reduced to 8after the successful application of the multi-level feature selection technique. With the help of these 8 features, the similarity match helps retrieve vehicles from recorded traffic videos as shown in Figure 3.

Table 1 Experimental Attributes

Attributes	**Features**
No.of Tested videos	183
Video category	Set1: High-density traffic rate Set2:Poorly-illuminated conditions Set3: Night-time videos

Video type	AVI format
Frame size	320x240

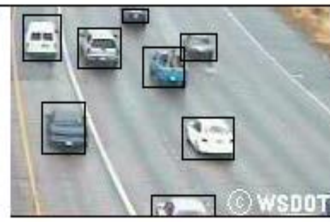
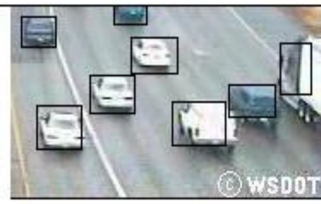
Vehicle Data base	Values match points	Tracked vehicle(Query)	Similarity measures level
	Data base Shape feaure values area: 401 minLength: 2.735877769889693e+001 perimeter: 2.251543289325509e+002 EquivDiameter: 2.259577521216744e+001 Data base GLCM feaure values Autocorrelation: 2.367862068965518e+001 Prominence: 5.672702318072098e+001 Shade: 1.629113300586308e+000 Variance: 2.501757172683190e+001		Similarity measure macth Query Shape feaure values area: 336 minLength: 2.006381326052847e+001 perimeter: 1.461837661840735e+002 EquivDiameter: 2.068353178330564e+001 Query GLCM feaure values Autocorrelation: 2.354769230769230e+001 Prominence: 5.329274054993594e+001 Shade: 1.663353503868953e+000 Variance: 2.507990760216347e+001
	Data base Shape feaure values area: 873 minLength: 3.044360682612632e+001 perimeter: 1.671126983722081e+002 EquivDiameter: 3.333973788969849e+001 Data base GLCM feaure values Autocorrelation: 4.119958419958420e+001 Prominence: 1.324333065105170e+002 Shade: -1.000328033587316e+001 Variance: 4.269852896390982e+001		Similarity measure macth Query Shape feaure values area: 859 minLength: 3.129797544993191e+001 perimeter: 1.739411254969543e+002 EquivDiameter: 3.307132850260940e+001 Query GLCM feaure values Autocorrelation: 4.065437860082305e+001 Prominence: 1.444242913371380e+002 Shade: -1.098124015648019e+001 Variance: 4.207193909947274e+001

Figure 3: Vehicle Retrieval based on similarity match

4.2 Performance Analysis

The measures used to determine system performance are precision, recall, F-score and accuracy. Precision and recall are determined, based on the number of context frames correctly separated. For vehicle retrieval the inquiry response time is most widely used method for analysing the performance of retrieval system. The inquiry response time is measured by the below mentioned concepts.

4.2.1 INQUIRY RESPONSE TIME.

The actual inquiry response time of vehicle retrieval system largely depends on number of attributes used for classification and response time of machine learning algorithm used. For a real time traffic environment, the timing requirement of the classifier to recognize the vehicles is highly important since the vehicles appeared in the frames only with some appropriate number of time and features extracted is also varying in larger scale. Here to prove the performance metrics of ED distance metric rule in vehicle retrieval process vehicles are assessed from a traffic video sequence and its features are automatically extracted and stored in database. Then online feature extraction system accomplishes matching process with data base values which is the combination of texture and shape information's. Evaluation of discrimination measurements is obtained through the comparison of vehicle search framework developed by Feris et al., as shown in table 6.12. By looking at vehicle search results associated with the similarity matching based query achieved 92% classification accuracy over 360 vehicles matched and retrieved.

Table 2: Performance measure of vehicle retrieval system

Performance measure	CMVRS (%)	Proposed Method (%)
Recall	**76**	**79**
Precision	**71**	**82**
F-score	**95**	**98**
Accuracy	**87**	**92**

The following tasks are reviewed and implemented prior to retrieval process:

- Train set with an adequate amount of attributes which are easy to handle with the known ED volume;
- Train set contains attributes from both texture and appearance (shape) model equally (4 from each).
- Maximize the system performance in such a way to handle the matching process based on its score value and
- Ability to add more space through indexing when the number of vehicles in scope increases.

5. Conclusions

- Mixed feature sets such as clear texture and shape attributes fit well with the vehi cle retrieval system. Changes in visual appearance regions have also been properl y classified, though the algorithm does not exactly detect them. In addition , rese arch may focus on developing new feature set
  based on color information which matches the vehicle exactly with similar color regions.

- The framework worked across different kinds of traffic videos containing multiple vehicles, shadow and occlusion.

- The system can able to retrieve vehicle of any shape and size.
- The above designed system reduces the computation cost as well as time
- Vehicles retrieved by the system match human levels of understanding and reduce the semantic gap.

References

1. Zexuan Zhu, Yew-Soon Ong& Manoranjan Dash 2007, 'Wrapper–filter feature selection algorithm using a memetic framework' IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) vol. 37, issue 1, pp. 70-76.
2. Gelzinis, Adas, AntanasVerikas &MarijaBacauskiene 2007, 'Increasing the discrimination power of the co-occurrence matrix-based features' Pattern Recognition, vol. 40, no. 9,pp. 2367-2372.
3. Heikkila Marko &MattiPietikainen 2006, 'A texture-based method for modeling the background and detecting moving objects' IEEE transactions on pattern analysis and machine intelligence, vol. 28, no. 4, pp. 657-662.
4. Weiqiang Wang,Datong Chen, Wen Gao &Jie Yang 2008, 'Modeling background and segmenting moving objects from compressed video' IEEE transactions on circuits and systems for video technology, vol. 18, issue 5, pp. 670-681.
5. Papathomas & Thomas V 1996, 'Guest Editorial' International Journal of Imaging Systems and Technology, vol. 7, no. 2,pp. 63-64.
6. Janecek, A, Gansterer, W, Demel, M & Ecker, G 2008, 'On the relationship between feature selection and classification accuracy' In New Challenges for Feature Selection in Data Mining and Knowledge Discovery pp. 90-105
7. Papageorgiou, Constantine P&TomasoPoggio 1999, 'A trainable object detection system: Car detection in static images'
8. Christos-Nikolaos E Anagnostopoulos,Ioannis E Anagnostopoulos ,Ioannis D Psoroulas, Vassili Loumos &Eleftherios Kayafas 2008, 'License plate recognition from still images and video sequences: A survey' IEEE Transactions on intelligent transportation systems, vol. 9, no. 3, pp. 377-391.
9. Hadi, Raad Ahmed, GhazaliSulong &LoayEdwar George 2014, 'Vehicle detection and tracking techniques: a concise review' arXiv preprint arXiv:1410.5894.
10. Hossein Tehrani Niknejad,Taiki Kawano,Mikio Shimizu&Seiichi Mita 2012, 'Vehicle detection using discriminatively trained part templates with variable size' In Intelligent Vehicles Symposium (IV), IEEE, pp. 766-771.

11. Huang, Jingchang, Xin Zhang, Qianwei Zhou, Enliang Song &Baoqing Li 2014, ‘A practical fundamental frequency extraction algorithm for motion parameters estimation of moving targets’ IEEE Transactions on Instrumentation and Measurement, vol. 63, no. 2, pp.267-276.
12. Jianqiang Wang,Xiaoyan Sun & Junbin Guo 2013, ‘A region tracking-based vehicle detection algorithm in nighttime traffic scenes’Sensors, vol. 13, no. 12,pp. 16474-16493.
13. Qian Zhang & King NgiNgan 2012, ‘Segmentation and Tracking Multiple Objects Under Occlusion From Multi view Video’. IEEE transactions on intelligent transportation systems, vol. 14, no. 2.
14. Reza, MdShamim & Jinwen Ma 2016, ‘ICA and PCA integrated feature extraction for classification’ Signal Processing (ICSP), IEEE 13th International Conference on.
15. Shengcai Liao,Guoying Zhao,Vili Kellokumpu, Matti Pietikäinen &Stan Z Li 2010, ‘Modeling pixel process with scale invariant local patterns for background subtraction in complex scenes’ In Computer Vision and Pattern Recognition (CVPR), IEEE Conference on
pp. 1301-1306.
16. Tao Wang & Zhigang Zhu 2012, ‘Real time moving vehicle detection and reconstruction for improving classification’ In Applications of Computer Vision (WACV), IEEE Workshop on, pp. 497-502. Wang, Jianqiang, Xiaoyan Sun &JunbinGuo 2013, ‘A region tracking-based vehicle detection algorithm in nighttime traffic scenes’Sensors, vol. 13, no. 12,pp. 16474-16493.
17. Wang, Jianqiang, Xiaoyan Sun &JunbinGuo 2013, ‘A region tracking-based vehicle detection algorithm in nighttime traffic scenes’Sensors, vol. 13, no. 12,pp. 16474-16493.
18. Xu, Wencong &Hai Liu 2011, ‘Vision-based multiple vehicle detection and tracking at nighttime’ In International Symposium on Photo electronic Detection and Imaging, pp. 81941B-81941B. International Society for Optics and Photonics.
19. Yunsheng Zhang,Chihang Zhao, Jie He &Aiwei Chen 2016, ‘Vehicles detection in complex urban traffic scenes using Gaussian mixture model with confidence measurement’ IET Intelligent Transport Systems, vol. 10, no. 6,pp. 445-452.
20. Zezhi Chen, Tim Ellis & Sergio A Velastin 2012, ‘Vehicle detection, tracking and classification in urban traffic.’ Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on. IEEE.