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Moving Object Detection using Segmentation Techniques

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Abstract

Moving object detection is the basic step for the analysis of video. It is the monitoring of the behavior, activities or other changing information and aims at background subtraction to locate the object position in video frame. A fast and accurate moving object detection technique is important to detect, recognize and track objects over a sequence of images. This research area has been studied for decades; many techniques have been reported and applied on different video surveillance applications. However, there are still some unsolved problems need to be addressed due to multiple objects present in the scene, whereby we wish to determine the position of the same object across time. These types of tasks require not only good initial object detection but reliable body part segmentation as well. Thresholding has found to be a well-known technique for background subtraction such that pixels labelled corresponds to object and 0 to background. Thresholding is further divide into the global and local thresholding techniques.

Keywords: *Video Frame, Local Thresholding, Global Thresholding, Otsu's Thresholding, Segmentation*

Nomenclature

I : Frame Data
FM : Frame Difference
FDM : Frame Difference Mask
BD : Background Difference
BI : Background Information
TCM : Texton Co-occurrence Matrix
BDM : Background Difference Mask
GLCM : Gray Level Co-occurrence Matrix
IOM : Initial Object Mask
SI : Stationary Index
BG : Background Indicator
IBG : Image Background Subtraction

Introduction

In video surveillance we try to detect, recognize and track objects over a sequence of images and it also makes an attempt to understand and describe object behavior by replacing the aging old traditional method of monitoring cameras by human operators. Object detection and tracking are important and challenging tasks in many computer vision applications such as surveillance, vehicle navigation and autonomous robot navigation. Object detection involves locating objects in the frame of a video sequence.

It handles segmentation of moving objects from stationary background objects. Commonly used techniques for object detection are background subtraction, statistical models, temporal differencing and optical flow. Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. Object tracking is the process of locating an object or multiple objects over time using a camera**.** The output produced by tracking step is generally used to support and enhance motion segmentation, object classification and higher level activity analysis. The final step of the smart video surveillance systems is to recognize the behaviors of objects and create high-level semantic descriptions of their actions.

Detection

The main aim of object detection is to distinguishing foreground objects from the stationary background. Almost the entire visual surveillance systems the first step is detecting foreground objects [12]. Short and long term dynamic scene changes such as repetitive motions (e.g. waiving tree leaves, light reflectance, shadows, camera noise and sudden illumination variations) make reliable and fast object detection difficult. It is a general idea that if an object is changing its position with respect to a point in the space, then it is considered to be moving. Rest scene is said to be the background. The movements of the object can be properly analyzed if object is detected accurately.

Background subtraction is a general term for a process which aims to segment moving foreground objects from a relatively stationary background. As illustrated in fig 1.1 there is an important distinction between the background modeling and background detection stages, which comprise the whole subtraction process. These two stages are often interrelated and sometimes overlapping. The modeling stage creates and maintains a model of the background scene. The detection process is responsible for segmenting the current image into moving (foreground) and stationary (background) regions based on the current background model. The resulting detection masks may then be fed back into the modeling process in order to avoid corruption of the background model by foreground object.

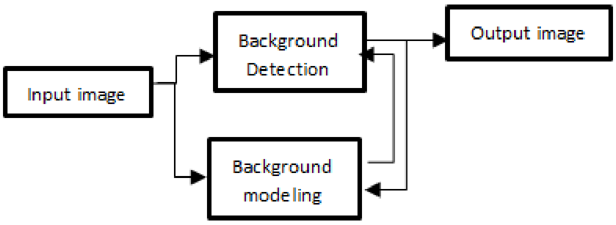

Figure 1.1: A video source produces images

The modeling stage uses previous video frames and detection results to maintain background model B. The detection stage compares the current frame to the current model to produce a detection mask E.

In order for the description to be characteristic of the true object, a reliable segmentation must be provided otherwise, errors in the detection stage will give rise to misrepresentation, which may result in misclassification.

Image Segmentation Techniques

In designing automated systems for the interpretation or manipulation of image data, system developers often need to perform software imaging operations, called segmentation [Fig. 1.3], that extract information about the structure of objects and to separate and discern various parameters of interest within the data

Fig 1.2 image

Fig 1.3 Segmented image

Clustering Methods

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is:

1. Pick K cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster center
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters)

In this case, variance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

In statistics and machine learning, the k-means algorithm is clustering algorithm to partition n objects into k clusters, where k < n. It is similar to the expectation-maximization algorithm for mixtures of Gaussians in that they both attempt to find the centers of natural clusters in the data. The model requires that the object attributes correspond to elements of a vector space. The objective it tries to achieve is to minimize total intra-cluster variance, or, the squared error function. The k-means clustering was invented in 1956. The most common form of the algorithm uses an iterative refinement heuristic known as Lloyd's algorithm. Lloyd's algorithm starts by partitioning the input points into k initial sets, either at random or using some heuristic data. It then calculates the mean point, or centroid, of each set. It constructs a new partition by associating each point with the closest centroid. Then the centroids are recalculated for the new clusters, and algorithm repeated by alternate application of these two steps until convergence, which is obtained when the points no longer switch clusters (or) alternatively centroids are no longer changed.

Edge Detection Method

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. Discontinuities are bridged if the distance between the two edges is within some predetermined threshold. One such method is the edge linking method, proposed by Pathegama and Gol.

Graph Partitioning Method

Graphs can effectively be used for image segmentation. Usually a pixel or a group of pixels are vertices and edges define the similarity among the neighborhood pixels. Some popular algorithms of this category are random walker, minimum mean cut, minimum spanning tree-17 based algorithm, normalized cut, etc. The normalized cuts method was first proposed by Shi and Malik in 1997. In this method, the image being segmented is modeled as a weighted, undirected graph. Each pixel is a node in the graph, and an edge is formed between every pair of pixels. The weight of an edge is a measure of the similarity between the pixels. The image is partitioned into disjoint sets (segments) by removing the edges connecting the segments. The optimal partitioning of the graph is the one that minimizes the weights of the edges that were removed (the cut). Shi's algorithm seeks to minimize the normalized cut, which is the ratio of the cut to all of the edges in the set.

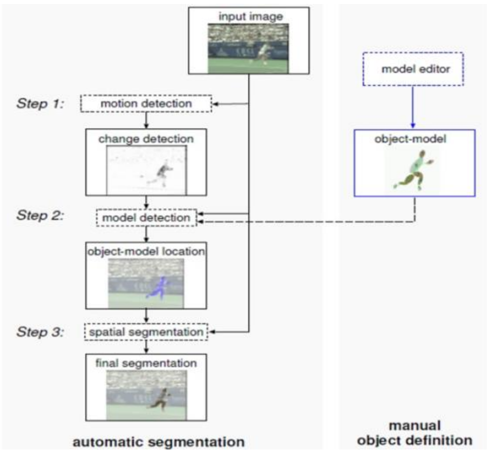

Fig.1.4 Image segmentation using graph partitioning method

Histogram Based Methods

Histogram-based [14] methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure. A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed. One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. In this technique of image classification distance metric and integrated region matching are familiar.

Global Thresholding Method

Thresholding is one of the most powerful and important tools for image segmentation. The segmented image obtained from thresholding has the advantages of smaller storage space, fast processing speed and ease in manipulation compared with gray level image which usually contains 256 levels. The thresholding techniques, which can be divided into bi-level and multilevel category. In bi-level thresholding [Fig.1.5(a)], a threshold is determined to segment the image into two brightness regions which correspond to background and object. Several methods have been proposed to automatically select the threshold. Otsu *et.al* formulates the threshold selection problem as a discriminant analysis where the gray level histogram of image is divided into two groups and the threshold is determined when the variance between the two groups is the maximum. Even in the case of unimodal histogram images, that is, the histogram of a gray level image does not have two obvious peaks, Otsu's method can still provide satisfactory result. Therefore, it is referred to as one of the most powerful methods for bi-level thresholding. In multilevel thresholding [Fig.1.5(b)], more than one threshold will be determined to segment the image into certain brightness regions which correspond to one background and several objects.

The selection of a threshold will affect both the accuracy and the efficiency of the subsequent analysis of the segmented image. The principal assumption behind the approach is that the object and the background can be distinguished by comparing their gray level values with a suitably selected threshold value. If background lighting is arranged so as to be fairly uniform, and the object is rather flat that can be silhouetted against a contrasting background, segmentation can be achieved simply by thresholding the image at a particular intensity level.

The simplicity and speed of the thresholding algorithm make it one of the most widely used algorithms in automated systems ranging from medical applications to industrial manufacturing. The binarized image is especially suitable as the input for hardware implementation of template matching through correlation and moment based recognition. Besides the application of thresholding in image segmentation, it is also used in various classification problems in pattern recognition. Suppose that the gray-level histogram shown in Fig 1.5(a) corresponds to an image, f(x; y), composed of light objects on a dark background, in such a way that object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold T that separates these modes. Then any (x; y) for which f(x; y) > T is called an object point; otherwise, the point is called a background point. Fig. 1.5(b) shows a slightly more general case of this approach, where three dominant modes characterize the image histogram (for example, two types of light objects on a dark background).

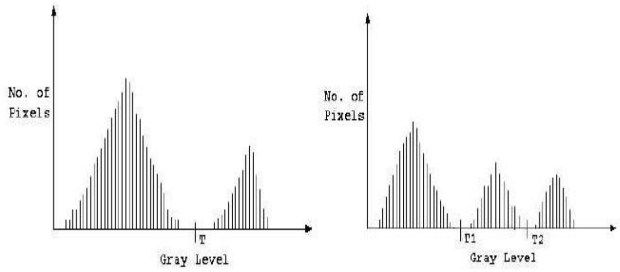

Fig.1.5 Gray-level histograms that can be partitioned by (a) a single threshold, and (b) multiple thresholds

Here, multilevel thresholding classifies a point (x; y) as belonging to one object class if T1 < f(x; y) >T2, to the other object class if f(x; y) > T2, and to the background if f(x; y)< T1. Based on the preceding discussion, thresholding may be viewed as an operation that involves tests against a function T of the form *T = T[x; y; p(x; y); f(x; y)]* where f(x; y) is the gray level of point (x; y) and p(x; y) denotes some local property of this point-for example, the average gray level of a neighborhood centered on (x; y). A threshold image g(x; y) is defined as

$$G(x,y) = \begin{cases} 0 - if - f(x,y), \leq T \\ 1 - if - f(x,y), > T \end{cases}$$

Thus, pixels labeled 1 (or any other convenient gray level) correspond to objects, whereas pixels labeled 0 (or any other gray level not assigned to objects) correspond to the background. When T depends only on f(x; y) (that is, only on gray-level values) the threshold is called global. If T depends on f(x; y) and p(x; y), the threshold is called local. If, in addition, T depends on the spatial coordinates x and y, the threshold is called dynamic or adaptive. One simple technique for finding a suitable threshold arises in situation where the proportion of the background that is occupied by objects is substantially constant in a variety of conditions. The technique that is most frequently employed for determining thresholds involves analyzing the histogram of intensity levels in the gray image.

This method is subject to the following major difficulties:
1. The valley may be so broad that it is difficult to locate a significant minimum.
2. There may be a number of minima because of the type of detail in the image, and selecting the most significant one will be difficult.
3. Noise within the valley may inhibit location of the optimum position.
4. There may be no clearly visible valley in the distribution because noise may be excessive or because the background lighting may vary appreciably over the image.
5. Either of the major peaks in the histogram (usually that dye to the background) may be much larger than the older, and this will then bias the position of the minimum.
6. The histogram may be inherently multimodal, making it difficult to determine which the relevant thresholding level is.

Otsu's global thresholding method

This method is a nonparametric and unsupervised method of automatic threshold selection for image segmentation. An optimal threshold is calculated by the discriminate criterion, namely, so as to maximize the between-class variance or to minimize the within-class variance. The method is very simple, utilizing only the zeroth and first order cumulative moments of the gray level histogram.

Let the pixels of a given image represented in *L* gray levels [1; 2; :::; L]. The number of pixels at level *i* is denoted by *ni* and the total number of pixels by *N = n1+n2+:::+nL.* For simplification, the gray-level histogram is normalized and regarded as a probability distribution.

$$P_i = \frac{ni}{N}, \quad P_i \geq 0, \quad \sum_{i=1}^{L} \mathrm{Pi} = 1 \qquad (1)$$

To emphasize the partitioned windows technique, only Otsu's thresholding method is considered among many other techniques. This method can be stated as follows: For a given image *f(x, y)* with m gray levels *0, 1, . . . ,m-1*, let the threshold be j, where *0< j< m-1*. Then, all pixels in image *f(x, y)* can be divided into two groups: group A with gray level values of pixels less than or equal to *j*; and group B with values greater than *j*. Also, let *(w1(j), M1(j)) (Eqn.2,3) (w2(j), M2(j)) (Eqn.4,5)* be the number of pixels and the average gray level value in group A and group B, respectively. Then

$$w_1(j) = \sum_{i=0}^{j} \mathrm{ni}, 0 \leq j \leq m-1 \qquad (2)$$

$$M_1(j) = \frac{\sum_{i=0}^{j}(i,\mathrm{ni})}{\mathrm{w1(j)}}, 0 \leq j \leq m-1 \qquad (3)$$

$$W_2(j) = \sum_{t=j+1}^{m-1} \mathrm{ni}, 0 \leq j \leq m-1 \qquad (4)$$

$$M_2(j) = \frac{\sum_{t=j+1}^{m-1}(\mathrm{i,ni})}{\mathrm{w2(j)}}, 0 \leq j \leq m-1 \qquad (5)$$

where n_i is the number of pixels with gray level value *i.* Expressing the average gray level value M_t (Eqn.6) of all the pixels in image *f(x, y)* as

$$M_t = \frac{\mathrm{w1(j)M1(j)+w2(j)\,M2(j)}}{\mathrm{w1(j)+w2(j)}} \qquad 0 \leq j \leq m-1 \qquad (6)$$

the variance between the two groups, denoted as $\sigma_B^2 B(j)$, is

$$\sigma_{B(j)}^2 = w1(j)(M1(j) - MT)2 + w2(j)(M2(j) - MT)2 \qquad (7)$$

$$= \frac{\mathrm{w1(j)w2(j)(M1(j) - M2(j))2}}{\mathrm{w1(j)+w2(j)}} \qquad (8)$$

For j ranging from 0 to m-1, calculate each $\sigma_{B(j)}^2$ Using above Eqn(7,8), and the value j corresponding to the greatest $\sigma_{B(j)}^2$ is the resulting threshold T.

One of the limitation of otsu's thresholding is that a lot of noise is visible in the background during video tracking and sometimes gave false tracking results.

Literature Review

D. Forsyth, P. Torr, *et.al* [4] proposed several inherent characteristics of natural outdoor environmental monitoring that pose a challenge to automated background modelling and subtraction is paid. Namely, foreground objects tend to, by necessity, blend into the background, and the background exhibits large variations due to non-stationary objects (moving leaves) and rapid transitions from light to shadow. These conditions present a challenge to the state of the art, which is addressed with an algorithm that exhibits comparable performance also on standard surveillance data sets. A side benefit of this approach is that it has relatively low memory requirements, does not require floating point operations, and for the most part, can run in parallel. This makes it a good candidate for embedded processing, where Single Instruction, Multiple Data (SIMD) processors are available.

CHI Jian-nan *et.al*.[5] reveals the image multi-scale edge detection based on anti-symmetrical bi-orthogonal wavelet is given detailed in theory. Especially an algorithm of wavelet decomposition in which multi-scale edge can be detected is put forward. Based on above using different kinds of wavelet decomposition data such as approximate coefficients and multi-scale edge image, a moving object detection approach in active video surveillance system is proposed. Firstly, Block Matching is used to calculate motion vector in low frequency image of wavelet decomposition. Then Motion Compensation and Frame difference between two adjacent frames applied to extract moving object information. And using multi-scale edge image of wavelet Region Growth is combined with Hough Transformation to define region of potential object. Finally, object is farther segmented in object potential region. Experimental results indicate that the method presented in the paper is effective.

Parisa Darvish Zadeh Varcheie *et.al*.[7] reveals a region-based method for background subtraction. It relies on color histograms, texture information, successive division of candidate rectangular image regions to model the background and detect motion. The proposed algorithm uses this principle and combines it with Gaussian Mixture background modelling to produce a new method which outperforms the classic Gaussian Mixture background subtraction method. The method has the advantages of filtering noise during image differentiation and providing a selectable level of detail for the contour of the moving shapes. The algorithm is tested on various video sequences and is shown to outperform state-of-the-art background subtraction methods.

Olga Zoidi *et.al*.[15] proposed that a visual object tracking framework, which employs an appearance-based representation of the target object, based on local steering kernel descriptors and color histogram information. This framework takes as input the region of the target object in the previous video frame and a stored instance of the target object, and tries to localize the object in the current frame by finding the frame region that best resembles the input. As the object view changes over time, the object model is updated, hence incorporating these changes. Color histogram similarity between the detected object and the surrounding background is employed for background subtraction. Experiments are conducted to test the performance of the proposed framework under various conditions. The proposed tracking scheme is proven to be successful in tracking objects under scale and rotation variations and partial occlusion, as well as in tracking rather slowly deformable articulated objects.

PranamJanney *et.al*.[17] had been proposed an intelligent machines require basic information such as moving-object detection from videos in order to deduce higher-level semantic information. A methodology that uses a texture measure to detect moving objects in video. The methodology is computationally inexpensive, requires minimal parameter fine tuning and also is resilient to noise, illumination changes, dynamic background and low frame rate. Experimental results show that performance of the proposed approach is higher than those of state-of-the-art approaches. A framework for vehicular traffic density estimation using ground object detection technique and present a comparison between the foreground object detection-based framework and the classical density state modeling based framework for vehicular traffic density estimation.

BargaDeori *et.al*.[19] proposed the ongoing research on object tracking in video sequences has attracted many researchers. Detecting the objects in the video and tracking its motion to identify its characteristics has been emerging as a demanding research area in the domain of image processing and computer vision. This paper proposed a literature review on the state of the art tracking methods, categorize them into different categories, and then identify useful tracking methods. Most of the methods include object segmentation using background subtraction. The tracking strategies use different methodologies like Mean-shift, Kalman filter, Particle filter etc. The performance of the tracking methods varies with respect to background information. In this survey, we have discussed the feature descriptors that are used in tracking to describe the appearance of objects which are being tracked as well as object detection techniques. In this survey, we have classified the tracking methods into three groups, and a providing a detailed description of representative methods in each group, and find out their positive and negative aspects.

Conclusion

This paper has focused on the moving object detection using segmentation techniques. Object Detection is the main thing in video surveillance. The main objective of this paper is to evaluating the short comings of algorithms for moving object detection. It has been found that each technique has its own benefits and limitations; no technique is best for every case. The main limitation of existing work is found to be that it is not good in separating the small moving things as background. In near future we will propose a new algorithm which will use more reliable methodology to enhance the work. We will propose a new algorithm which will use multi background registration technique to improve the results further.

References

[1] Weilong Chen, Meng JooEr, Member, IEEE, and Shiqian Wu, Member, IEEE, "Illumination Compensation and Normalization for Robust Face Recognition Using Discrete Cosine Transform in Logarithm Domain" IEEE Transactions On Systems, Man, And Cybernetics—Part B: Cybernetics, Vol. 36, No. 2, April 2006

[2] Harsha Varwani Heena Choithwani, "Understanding various Techniques for Background Subtraction and Implementation of Shadow Detection" IJCTA Vol 4 (5),822-827,2006

[3] Virendra P. Vishwakarma, Sujata Pandey Member IEEE, and M. N. Gupta, "A Novel Approach for Face Recognition Using DCT Coefficients Re-scaling for Illumination Normalization" 15th International Conference on Advanced Computing and Communications © 2007 IEEE

[4] D. Forsyth, P. Torr, and A. Zisserman (Eds.): ECCV 2008, Part III, LNCS 5304, pp. 276–289, 2008 ©Springer-Verlag Berlin Heidelberg 2008

[5] CHI Jian-nan, ZHANG Chuang, ZHANG Han, LIU Yang, YAN Yan-Tao, "Approach of Moving Objects Detection in Active Video Surveillance" Joint 48th IEEE Conference on Decision and Control and 28th Chinese Control Conference Shanghai, P.R. China, December 16-18, 2009

[6] Caius SULIMAN, Cristina CRUCERU, Florin MOLDOVEANU, "Kalman Filter Based Tracking in a Video Surveillance System" 10th International Conference on Development and Application Systems, Suceava, Romania, May 27-29, 2010

[7] Parisa Darvish Zadeh Varcheie, Michael Sills-Lavoie and Guillaume-Alexandre Bilodeau, "A Multiscale Region-Based Motion Detection and Background Subtraction Algorithm" Sensors 2010, ISSN 1424-8220, 1041-1061

[8] Prashant P. Baveja, Drew N. Maywar, Member, IEEE, Aaron M. Kaplan, and Govind P. Agrawal, Fellow, IEEE "Self-Phase Modulation in Semiconductor Optical Amplifiers: Impact of Amplified Spontaneous Emission" IEEE journal of quantum electronics, VOL. 46, NO. 9, SEPTEMBER 2010

[9] Virendra P. Vishwakarma, Sujata Pandey and M. N. Gupta, "An Illumination Invariant Accurate Face Recognition with Down Scaling of DCT Coefficients" Journal of Computing and Information Technology - CIT 18, 2010, 1, 53–67

[10]Vinayak G Ukinkar, Makrand Samvatsar, "Object detection in dynamic background using image segmentation: A review" IJERA, ISSN: 2248-9622 Vol. 2, Issue 3, May-Jun 2012, pp.232-236

[11]Kalyan Kumar Hati, Pankaj Kumar Sa, and Banshidhar Majhi, "Intensity Range Based Background Subtraction for Effective Object Detection" IEEE Signal Processing Letters, Vol. 20, No. 8, August 2013,Pp759-762

[12]Hemavathy R, Dr. Shobha G, "Object Detection and Tracking under Static and Dynamic environment: A Review" International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 10, October 2013pp4095-4100

[13]Deepak Kumar Rout, Sharmistha Puhan, "Video Object Detection in Dynamic Scene using Inter-Frame Correlation based Histogram Approach" International Journal of Computer Applications (0975 – 8887) Volume 82 – No 17, November 2013, pp19-24

[14]Farah Yasmin Abdul Rahman, AiniHussain, WanMimiDiyanaWanZaki, HalimahBadiozeZaman, and NooritawatiMdTahir, "Enhancement of Background Subtraction Techniques Using a Second Derivative in Gradient Direction Filter" Hindawi Publishing Corporation Journal of Electrical and Computer Engineering Volume 2013

[15]Olga Zoidi, Anastasios Tefas, Member, IEEE, and Ioannis Pitas, Fellow, IEEE "Visual Object Tracking Based on Local Steering Kernels and Color Histograms" IEEE transaction on circuits and system for video technology VOL:25 NO:3 YEAR 2013.

[16]Bo Liu, Yan Lin, Guan Guan, "A Method of Multi-scale Edge Detection for Underwater Image" Journal of Information & Computational Science 10: 2 (2013) 345–354

[17]Pranam Janney and Glenn Geers, "A Robust Framework for Moving-Object Detection and Vehicular Traffic Density Estimation" Arxiv:1402.0289v1 [Cs.CV] 3 Feb 2014

[18]Saranya M*, Padmavathi S** "Face Tracking in Video by Using Kalman Filter" Saranya M Int. Journal of Engineering Research and Applications ISSN: 2248-9622, Vol. 4, Issue 6(Version 3), June 2014, pp.54-58.

[19]Barga Deoriand Dalton Meitei Thounaojam "A Survey on object tracking in video" International Journal on Information Theory (IJIT), Vol.3, No.3, July 2014

[20]Malik M. Khan, Tayyab W. Awan, Intaek Kim, and YoungsungSoh, "Tracking Occluded Objects Using Kalman Filter and Color Information" International Journal of Computer Theory and Engineering, Vol. 6, No. 5, October 2014

[21]Y.-P. Guan, "Motion Objects Segmentation and Shadow Suppressing without Background Learning" Hindawi Publishing Corporation Journal of Engineering Volume 2014

[22]Amr M. Nagy1, Ali Ahmed2 and Hala H. Zayed3 "A Robust approach of object tracking based on particle filter and optimised likelihood" International Journal of Emerging Technologies in Computational and Applied Sciences (IJETCAS)

[23]Horst Eidenberger "Illumination-invariant Face Recognition by Kalman Filtering" Vienna University of Technology, Favoritenstrasse 9-11, 1040Vienna, Austria.

[24] Brendan Klare, SudeepSarkar "Background Subtraction in Varying Illuminations Using an Ensemble Based on an Enlarged Feature Set" Dept of Computer Science and Engineering University of South Florida.

[25] Hua Yang Greg Welch Marc Pollefeys "Illumination Insensitive Model-Based 3D Object Trackingand Texture Refinement" Computer Science DepartmentUniversity of North Carolina at Chapel Hill.

[26] Dwarikanath Mahapatra1, Mukesh Kumar Saini2 and Ying Sun1 "Illumination Invariant tracking in office environment using neirobiology-saliency based particle filter" National University of Singapore.

[27]Christian Ku¨ blbeck*, Andreas Ernst "Face detection and tracking in video sequences using the modified census transformation" Department of Electronic Imaging, Fraunhofer Institute for Integrated Circuits, Am Wolfs mantel 33, 91058 Erlangen, Germany

[28] Stephen Se, David Lowe, Jim Little "Vision-based Mobile Robot Localization And Mapping using Scale-Invariant Features" Department of Computer Science University of British Columbia Vancouver, B.C. V6T 1Z4, Canada.

[29]Teresa Ko, Stefano Soatto, and Deborah Estrin "Background Subtraction on Distributions Vision" Lab Computer Science Department University of California, Los Angeles405 Hilgard Avenue, Los Angeles – CA 90095

[30] Wei-Kai Chan and Shao-Yi Chien "Real-Time Memory-Efficient Video Object Segmentation in Dynamic Background with Multi-Background Registration Technique" Graduate Institute of Electronics Engineering and Department of Electrical Engineering National Taiwan University.