Dhinaharan Nagamalai Ashok Kumar Annamalai Annamalai (Eds.)

# **Advances in Computational Science, Engineering and Information Technology**

Proceedings of the Third International Conference on Computational Science, Engineering and Information Technology (CCSEIT-2013), KTO Karatay University, June 7–9, 2013, Konya, Turkey – Volume 1



# Advances in Intelligent Systems and Computing

Volume 225

*Series Editor*

J. Kacprzyk, Warsaw, Poland

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Proceedings of the Third International Conference on Computational Science, Engineering and Information Technology (CCSEIT-2013), KTO Karatay University, June 7–9, 2013, Konya, Turkey – Volume 1



*Editors*

Dhinaharan Nagamalai Dept. of Computer Engineering Faculty of Engineering KTO Karatay University Konya **Turkey** 

Ashok Kumar School of Computing and Informatics University of Louisiana at Lafayett Louisiana **USA** 

Annamalai Annamalai Dept. of Electrical and Computer Engineering Prairie View A & M University Texas USA

ISSN 2194-5357 ISSN 2194-5365 (electronic)<br>ISBN 978-3-319-00950-6 ISBN 978-3-319-00951-3 ISBN 978-3-319-00951-3 (eBook) DOI 10.1007/978-3-319-00951-3 Springer Cham Heidelberg New York Dordrecht London

Library of Congress Control Number: 2013939955

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## **Preface**

The Third International Conference on Computational Science, Engineering and Information Technology (CCSEIT-2013) was held in Konya, Turkey, June 7–9, 2013. CCSEIT-2013 attracted many local and international delegates, presenting a balanced mixture of intellect from the East and from the West. The goal of this conference series is to bring together researchers and practitioners from academia and industry and share cutting-edge development in the field. The conference will provide an excellent international forum for sharing knowledge and results in theory, methodology and applications of Computational Science, Engineering and Information Technology. Authors were invited to contribute to the conference by submitting articles that illustrate research results, projects, survey work and industrial experiences describing significant advances in various areas of Computational Science, Engineering and Information Technology.

The CCSEIT-2013 Committees rigorously invited submissions for many months from researchers, scientists, engineers, students and practitioners related to the relevant themes and tracks of the conference. This effort guaranteed submissions from an unparalleled number of internationally recognized top-level researchers. All the submissions underwent a strenuous peer-review process which comprised expert reviewers. These reviewers were selected from a talented pool of Technical Committee members and external reviewers on the basis of their expertise. The papers were then reviewed based on their contributions, technical content, originality and clarity. The entire process, which includes the submission, review and acceptance processes, was done electronically. All these efforts undertaken by the Organizing and Technical Committees led to an exciting, rich and a high quality technical conference program, which featured high-impact presentations for all attendees to enjoy, appreciate and expand their expertise in the latest developments in computer network and communications research.

In closing, CCSEIT-2013 brought together researchers, scientists, engineers, students and practitioners to exchange and share their experiences, new ideas and research results in all aspects of the main workshop themes and tracks, and to discuss the practical challenges encountered and the solutions adopted. We would like to thank the General and Program Chairs, organization staff, the members of the Technical Program Committees and external reviewers for their excellent and tireless work. We sincerely

wish that all attendees benefited scientifically from the conference and wish them every success in their research.

It is the humble wish of the conference organizers that the professional dialogue among the researchers, scientists, engineers, students and educators continues beyond the event and that the friendships and collaborations forged will linger and prosper for many years to come. We hope that you will benefit from the fine papers from the CCSEIT-2013 conference that are in this volume and will join us at the next CCSEIT conference.

> Dhinaharan Nagamalai Ashok Kumar Annamalai Annamalai

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## **Urban Traffic Management System by Videomonitoring**

José [Ran](http://www.zuq.com.br)iery Ferreira Junior

ZUQ - Intelligent Transportation Lourival Melo Mota Ave, 12 Building, 107 Room, Federal University of Alagoas Tabuleiro dos Martins, Maceió, Alagoas, Brasil, 57072-970 Institute of Computing, Master's Program in Informatics Federal University of Alagoas jose.raniery@gmail.com http://www.zuq.com.br

Abstract. As the big cities grow, it's more necessary the use of cameras for urban traffic monitoring. The increase in the number of vehicles on the streets makes the traffic congestion, one of the largest metropolis problems, even more often to happen. To avoid this kind of issue, this paper proposes a management system by videomonitoring for the urban traffic. And the goal is to identify the vehicles e count them in period of time using Computer Vision and Image Processing techniques.

**Keywords:** videomonitoring, urban tra[ffic,](#page-26-0) computer vision.

#### **1 Introduction**

Vehicle detection through videomonitoring is a important tool for real time traffic management systems. It offers some advantages against the traditional methods, such as loop detectors. Besides vehicle count, video images can provide more informations about the traffic: speed and vehicle classification [3].

So it's expectated the decrease of the congestion in the big cities and the number of accidents in the urban roads, big issues that metropolis in the whole worl[d h](#page-26-0)ave to face.

The presence of Graphics [Co](#page-26-1)[mp](#page-26-2)uter in t[he](#page-26-3) [hu](#page-26-4)man day-by-day is increasing, and even more Computer Vision and Image Processing. The computers and cameras prices are the lowest ever seen and it gets more viable to equip the roads with an artificial vision system that is able to detect movements, follow vehicle track and extract informations, such as speed, dimensions and traffic density [1].

Some useful algorithms for vehicle detection in the literature were: background classification learning [3], image segmentation [1], application of mathematical morphology operations, such eroding and dilation [4], others [5] [2].

The goal of this paper is to develop a system that aids the traffic management of main urban roads and aim to decrease the number of vehicles. This way, the expectation is the congestions end by means of vehicle detection and count.

D. Nagamalai et al. (Eds.): *Adv. in Comput. Sci., Eng. & Inf. Technol.*, AISC 225, pp. 1–9. DOI: 10.1007/978-3-319-00951-3\_1 c Springer International Publishing Switzerland 2013

As secondary goal, it expects that the algorithm has low processing cost, using opensource tools.

#### **2 Methods**

All video samples used in this sys[tem](#page-26-5) had speed rate of 30 frames per seconds and dimensions 640x480 coloured pixels.

The system was developed in Java 1.7 programming language, along with OpenCV (Open Source Computer Vision) version 2.4.0 graphic library with a wrapper to Java called JavaCV. OpenCV is an opensource library useful in [sev](#page-20-0)eral areas and techniques, as Computer Vision, Image Processing and Segmentation, Machine Learning, and others [6].

The system runs some steps, listed below. Bradski [7] affirms that the Warping operation is a geometric transformation based on image not uniform resizing. The Figure 1 shows a Warping operat[ion ex](#page-20-1)ample. In the system algorithm case, four points of the image are selected to form a trapezoid. This trapezoid corresponds to the frame's region of interest (ROI). The ROI is the image area where vehicle recognition happens. In the system case, only part of the street is the region of interest (Figure  $2(a)$ ). Vehicles that are far away are harder to identify, because of the proximity of itself and other vehicle. The areas that correspond to the sidewalk and the begin of the street are not of interest for processing. After the trapezoid's definition, the Warping operation is done and the image becomes the whole area corresponding to the trapezoid (Figure 2(b)).

- 1. Warping of the region of interest of the frame
- 2. Image conversion in grayscale
- 3. Background removal
- 4. Image binarization
- 5. Eroding and Dilation application
- 6. Contour areas detection
- 7. Count of the areas

Following, the image conversion in grayscale is performed, a necessary step to achieve better results in posterior steps (binarization e.g.). After that, the image bac[kgrou](#page-21-0)nd is removed, to identify only the moving objects (vehicles). This operation is performed by the OpenCV's function cvAbsDiff. This function performs the subtraction of two images (original e background), resulting the foreground. After that, the binarization operation is performed, so the image is segmented with 128 threshold, resulting in a black and white image (Figure  $3(a)$ ).

The mathematical morphology operations, eroding e dilation, are executed in sequence to eliminate isolated "spots" that do not make part of a vehicle and to group the "spots", respectively, that make part of the same vehicle, but somehow are separated (Figure 3(b)).

The localization of white "spots" contours is the next step of the algorithm. It is done by the OpenCV's function cvFindContours. As it was locating the "spots" frame by frame, it was able to perform the vehicle count by following:



<span id="page-20-1"></span><span id="page-20-0"></span>(a) Original Image (b) Image after Warping operation

**Fig. 1.** Warping Operation



(a) ROI marked by red trapezoid (b) Image after Warping operation of the ROI

**Fig. 2.** Warping of the region of interest of the frame

when a new vehicle "is born" in the frame, a rectangle is designed and the vehicle is put within it. After that, the vehicle is followed until the last frame which the "spot" appears. By the moment the rectangle is designed, it is calculated the rectangle centroid or its central point (see Formula 1). When a centroid crosses the counting line, a new vehicle is registered and counted.

$$
xCentroid = \frac{w}{2} + x;
$$
  

$$
yCentroid = \frac{h}{2} + y;
$$

**Formula 1.** Point (xCentroid, yCentroid) of the rectangle's centroid.

The centroid is a point (xCentroide, yCentroide), and this point is calculated by the formula above, where  $(x,y)$  is the far left and high point of the "spots" rectangle, w is the rectangle width and h is the height.

<span id="page-21-0"></span>

(a) Binary image of moving vehicles (b) Binary image after the morphological operations

**Fig. 3.** Result of morphological operations in a binary image

After the "birth" of a "spot", it is attributed an id to it. In the next frame, it is checked if thi[s](#page-23-0) centroid is located in the rectangle interior of some "spot" in the previous frame. If it is, that's because it's the same "spot", than it is the same id. If it's not, than it's a new one, than it's attributed a new id for it.

#### **2.1 Shadow Removal**

Shadows can cause some problems in background subtraction and vehicle detection, as you can see in Section 3 (Results and Discussion) of this paper. The detection of cast shadows as foreground objects is very common, producing undesirable consequences: shadows can connect different people walking in a group, generating a single object as output of background subtraction [8], but there's a technique in literature that can eliminate them of the grayscale image. Jacques [8] affirms that the normalized cross-correlation (NCC) can be useful to detect shadow pixel candidates.

As Jacques [8] described,  $B(i,j)$  is the background image and  $I(i,j)$  is an image of the video sequence. For each pixel  $(i,j)$  belonging to the foreground, consider a  $(2N + 1)$  X  $(2N + 1)$  template  $T_{ij}$  such that  $T_{ij}(n, m) = I(i + n, j + m)$ , for  $-N \leq n \leq N$ ,  $-N \leq m \leq N$  ( $T_{ij}$  corresponds to a neighborhood of pixel  $(i,j)$ ). Then, the NCC between template  $T_{ij}$  and image B at pixel  $(i,j)$  is given by Formula 2:

$$
NCC(i, j) = \frac{ER(i, j)}{E_B(i, j)E_{Tij}},
$$

where

$$
ER(i, j) = \sum_{n=-N}^{N} \sum_{m=-N}^{N} B(i+n, j+m)T_{ij}(n, m),
$$

$$
E_B(i,j) = \sqrt{\sum_{n=-N}^{N} \sum_{m=-N}^{N} B(i+n, j+m)^2}, and
$$

$$
E_{Tij} = \sqrt{\sum_{n=-N}^{N} \sum_{m=-N}^{N} T_{ij}(n, m)^2}.
$$

**Formula 2.** Normalized cross-correlation in a point (i, j).

A pixel  $(i,j)$  is pre-considered shadow if:

$$
NCC(i, j) \ge L_{ncc}
$$
  
and

$$
E_{Tij} < E_B(i,j)
$$

**Formula 3.** Condition for a point (i, j) to be pre-considered shadow.

where  $L_{ncc}$  is a fixed threshold. In this system,  $N = 4$  and  $L_{ncc} = 0.999$ . Then, pixels that are false positive are eliminated. This stage consists of verifying if the ratio  $I(i, j)/B(i, j)$  in a neighborhood around each shadow pixel candidate is approximately constant, by computing the standard deviation of  $I(i,$ j)/ $B(i, j)$  within this neighborhood. More specifically, we consider a region R with  $(2M+1)(2M+1)$  pixels (it was used  $M = 1$  in all experiments) centered at each shadow pixel candidate  $(i, j)$ , and classify it as a shadow pixel if:

$$
std_R(\frac{I(i,j)}{B(i,j)}) < L_{std}
$$
\n
$$
and
$$

$$
L_{low} \leq \left(\frac{I(i,j)}{B(i,j)}\right) < 1
$$

**Formula 4.** Condition to a point (i, j) to be a shadow pixel.

where  $\text{std}_R(\frac{I(i,j)}{B(i,j)})$  is the standard deviation of quantities  $I(i,j)/B(i,j)$  over the region R, and  $\tilde{L}_{std}$ ,  $L_{low}$  are thresholds. In this system, it was used  $L_{std} = 0.05$ and  $L_{low} = 0.3$ . Then it was applied morphological operations to enhance the results. As experiment, it was used a frame with three "spots", and after the shadow removal algorithm has been applied, the "spots" decreased the area in 25%, 18% and 19%, as it can be seen in Figure 4.

Despite this results, the shadow removal algorithm was not used in the main one because it demands much processing time (it takes some seconds to process a single frame), and one of the goals of the system is to have a low processing cost. So the algorithm will be enhanced, so in the future it can be used in the main algorithm.

<span id="page-23-0"></span>

(a) "Spots" before shadow removal algo-(b) "Spots" after shadow removal algorithm rithm

<span id="page-23-1"></span>**Fig. 4.** Result of shadow removal

#### **3 Results and Discussion**

Figure 5 shows a frame completely processed, so it was p[erf](#page-23-1)ormed all the described operations before, needed to recognize vehicles. In the Figure 5, six vehicles are shown, all identified (with rectangle and centroid), but only two were counted, both inferior, as only their centroids were below the counting line (green colour). In the next frame, if these same vehicles are still in the frame, they are not counted again. If other vehicle's centroid crosses the line, it will be counted one more vehicle.

It was performed tests with three video sample. The results are in the Table 1. It was computed the processing times of vehicle detection for each frame. The PMAI column of the table shows the biggest time taken by a frame to detect all vehicles. PMEN is the lowest time and PMED, the mean time of all frames of the sample. The NVT column of the table is the total number of vehicles the is shown in the video sample, independent if the vehicle crossed the counting line or not. NVM is the total number of vehicles that crossed the counting line, under manual count. The number of vehicles that crossed the green line that were counted by the algorithm can be seen by the NVA column.

	Sample Duration Number of frames PMAI PMEN PMED NVT NVM NVA						
15 s	450	41 ms	$5 \text{ ms}$	9 ms	23		
30 s	900	$32 \text{ ms}$	$5 \text{ ms}$	5 ms	97	22	
60 s	.800	$49 \text{ ms}$	$5 \text{ ms}$	ms	74	69	63

**Table 1.** Sample results

The sample 1 showed a processing mean bigger than all samples, but all the vehicles that crossed the counting line were counted. Just two vehicles stayed



**Fig. 5.** Recognition of vehicles in a frame

above the counting line, so that they were not registered. In sample 2, video duration was bigger, but the processing time for the recognition of the vehicles was lower, considering that its mean was 5 milliseconds, against 9 milliseconds for the first sample. It was counted 27 vehicles in total, but only 22 crossed the counting line.

The sample 3 had bigger video duration, and still a processing time mean lower than the sample 1. That means that sample 1 reached a bigger number of "spots" by frame than all others samples, but by the time the time duration was lower than the others, the number of vehicles also was lower.

Still about the sample 3, it was counted 74 vehicles manually, but only 69 could be counted because they were below the counting line. The algorithm counted 63 vehicles below the line.

Some error cases in the algorithm were found, such:

- **–** "Spots" inside others are not considered;
- **–** "Spots" with small areas, that are not vehicles, are not counted;
- **–** "Spots" with large width (likely two cars side by side that were not separated), the area was divided in two, so it will count two vehicles;
- **–** Vehicles that "are born" with two "spots" and than become one, is counted only once (the algorithm counts two times because of the two initial "spots");
- **–** Vehicles that "are born" with one spot and then becomes two, are counted only once.

Nevertheless, in this last case, there is a problem: when two vehicles are too close to each other in the "birth", only one "spot" is considered because of the shadow of both. After a while, much times the "spot" of two vehicles splits. So,

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by the previous rule, it will not count the second car as a new one, considering that only one "spot" in the beginning.

#### **3.1 Tests**

To test the accuracy of the algorithm, it was cr[ea](#page-25-0)ted a comparison mechanism of the manual and the algorithm count. Given a short interval of time, five seconds e.g., it is counted the number of vehicles, both manually and by the algorithm, that crosses the counting line. Then these counts are compared and it is obtained some indicators, like: difference between the manual and the algorithm counts, the total number of errors of the algorithm, the interval of time that has the larger number of errors, absolut mean, relative mean, variance and standard deviation of the errors, among others.

Some of these results and indicators are listed below in Table 2:

#### <span id="page-25-0"></span>**Table 2.** Tests results



NIE column represents the number of intervals that have errors in the whole video sample. TNE is total number of erro[rs](#page-23-1) in all intervals. AME and RME are the absolute and the relative mean of errors that a interval has, respectively. SD is the standard deviation of all errors in the video sample.

#### **4 Conclusion**

This paper presents a systems with low processing cost algorithm and success rate of 90% like showed in the three video samples in Table 1. Also it has good perspectives for the future to enhance the algorithm, considering that shadow removal technique achieved good initial results.

To obtain a bigger success rate, the ideal view would be a camera in the vertical position or 90 degrees angle towards the street and not diagonal, like presented in the video samples. So that, vehicles very close to each other would not be connected in a non appropriated way.

The disadvantages of the algorithms are: the need to obtain a background image manually and the difficulty to separate vehicles that are very close to each other. For future works, it is proposed an algorithm to eliminate the image background automatically and to integrate the shadow algorithm to the main one.

#### <span id="page-26-4"></span><span id="page-26-3"></span><span id="page-26-2"></span><span id="page-26-1"></span><span id="page-26-0"></span>**References**

- <span id="page-26-5"></span>1. Haupt, A.G.: Detecção de Movimento, Acompanhamento e Extração de Informações de Objetos Móveis. Universidade Federal do Rio Grande do Sul (2004)
- 2. Gupte, S., Masoud, O., Martin, R.F.K., Papanikolopoulos, N.P.: Detection and Classification of Vehicles. IEEE Transactions on Intelligent Transportation Systems (2002)
- 3. Tan, X., Li, J., Liu, C.: A video-based real-time vehicle detection method by classified back[ground learning. World Transactions on En]( http://opencv.willowgarage.com/wiki/)gineering and Technology Education (2002)
- 4. Purnama, I.K.E., Zaini, A., Putra, B.N., Hariadi, M.: Real Time Vehicle Counter System for Intelligent Transportation System. In: International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering (2009)
- 5. Daigavane, P.M., Bajaj, P.R.: Real Time Vehicle Detection and Counting Method for Unsupervised Traffic Video on Highways. International Journal of Computer Science and Network Security (2010)
- 6. OpenCV Official Homepage, http://opencv.willowgarage.com/wiki/ (last access: July 26, 2012)
- 7. Bradski, G., Kaehler, A.: Learning OpenCV Computer Vision with the OpenCV Library. O'Reilly Publisher (2008)
- 8. Jacques Jr., J.C.S., Jung, C.R.: Background Subtraction and Shadow Detection in Grayscale Video Sequences. In: Proceedings of the XVIII Brazilian Symposium on Computer Graphics and Image Processing (2005)

## **Symbolic Classification of Traffic Video Shots**

Elham Dallalzadeh<sup>1</sup>, D.S. Guru<sup>2</sup>, and B.S. Harish<sup>3</sup>

<sup>1</sup> Department of Computer, Marvdasht Branch, Islamic Azad University, Marvdasht, Iran elhamdallalzadeh@gmail.com <sup>2</sup> Department of Studies in Computer Science, University of Mysore, Manasagangothri, Mysore - 570 006, Karnataka, India dsg@compsci.uni-mysore.ac.in <sup>3</sup> Department of Information Science and Engineering, S J College of Engineering, Mysore, Karnataka, India

bharish@ymail.com

**Abstract.** In this paper, we propose a symbolic approach for classification of traffic video shots into light, medium, and heavy classes based on their content (congestion). We propose to represent a traffic video shot by an interval valued features. Unlike the conventional methods, the interval valued feature representation is able to preserve the variations existing among the extracted features of a traffic video shot. Based on the proposed symbolic representation, we present a symbolic method of classifying traffic video shots. The symbolic classification method makes use of a symbolic similarity measure for classification. An experimentation is carried out on a benchmark traffic video database. Experimental results reveal the efficacy of the proposed symbolic classification model. Moreover, it achieves classification within negligible time as it is based on a simple matching scheme.

**Keywords:** Traffic congestion, classification of traffic video shots, symbolic representation, interval valued features, symbolic similarity measure, symbolic classifier.

#### **1 Introduction**

Traffic congestion is a serious issue in many urban streets and highways. In order to reduce the traffic congestion, traditional solutions have been employed that are based on increasing the supply of roads. However, such solutions are costly. Furthermore, it is not always possible to employ because of the lack of suitable lands. Recently, interest has been grown up in optimizing the throughput [of](#page--1-0) the existing roads using visionbased traffic monitoring systems.

Vision-based traffic video monitoring systems help us in gathering statistical data on traffic activity through monitoring the density of vehicles. Furthermore, it assists taking intelligent decisions and actions in any abnormal conditions by analyzing the traffic information. Hence, an intelligent automated monitoring system can detect

D. Nagamalai et al. (Eds.): *Adv. in Comput. Sci., Eng. & Inf. Technol.*, AISC 225, pp. 11–22. DOI: 10.1007/978-3-319-00951-3\_2 © Springer International Publishing Switzerland 2013

traffic jams and divert vehicles from congested roads to less crowded ones. On the other hand, it is a key task to collect information on traffic flows in real-time.

Most of the information required for classification of traffic video shots can be based on motion that each traffic video contains. Thus, a holistic representation can be used to capture the variability of the motion without the need for segmenting or tracking individual components.

Yu et al., [2] presented a novel algorithm to directly extract highway traffic information such as average vehicle speed and density from MPEG compressed Skycam video. The MPEG motion vector field is filtered to remove vectors that are not consistent with vehicle motion. The traffic flow is then estimated by averaging the remaining motion vectors.

Porikli and Li [3] proposed an unsupervised, low-latency traffic congestion estimation algorithm that operates on the MPEG video data. Congestion features are directly extracted from the compressed domain. Gaussian Mixture Hidden Markov Models (GM-HMM) is employed to detect traffic congestion. Traffic patterns are detected as five traffic patterns (empty, open flow, mild congestion, heavy congestion, and stopped).

A framework to collect traffic flow information from urban traffic scenes is proposed by Lee and Bovik [1]. The traffic flow is presented by defining traffic regions. Basic statistics of traffic flow vectors inside the traffic regions are then computed.However, extracting reliable measurements of flow is difficult in traffic scenarios due to environmental conditions. Moreover, the extracted measurements are subjected to noise.

Chan and Vasconcelos [4] proposed an approach to model the entire motion field as a dynamic texture. It is an auto-regressive stochastic process with both spatial and temporal components. The auto-regressive stochastic process encodes the appearance and the underlying motion separately into two probability distributions. Distances among dynamic textures are computed using information theoretical measures of divergence (Kullback-Leibler divergence) between the associated probability distributions or through geometry measures based on their observable space (Martin distance). With these distance measures, the traffic congestion is classified using a Nearest Neighbor (NN) classifier or by the use of a Support Vector Machine (SVM) classifier with the Kullback-Leibler kernel. However, the proposed model is computationally complex. It cannot be well-adopted for on-line and real-time estimation of traffic congestion.

Derpanis and Wildes [5] described a system based on 3D spatio-temporal oriented energy model of dynamic texture. Traffic patterns are classified in terms of their dynamics measures aggregated over regions of image space-time. For such purposes, local spatio-temporal orientation is derived. Each traffic scene is then associated with a distribution (histogram) of measurements. Classification is performed based on matching such distributions (or histograms) of space-time orientation structure. However, heavy traffic in which the traffic stopped completely cannot be distinguished from light traffic with almost an empty (stationary) roadway.

The above mentioned issues motivate us to propose a simple yet efficient model to classify traffic video shots based on their content (congestion). We outline a novel method of representing and classifying traffic video shots using symbolic data analysis concepts.

The remaining part of the paper is organized as follows. In section 2, we discuss the proposed model for symbolic representation and classification of traffic video shots. The details of an experimentation conducted to demonstrate our proposed model on UCSD benchmark traffic video database are given in section 3. The paper is concluded in section 4.

#### **2 Proposed Model**

In this section, we outline a novel method of representation and classification of traffic video shots based on their content (congestion) using symbolic data concepts. Initially, each traffic video shot is filtered using Gabor filter to segment the texture content of its frame sequence. We make use of motion, appearance, and texture features as the conventional features to construct feature matrices for the frame sequence of a traffic video shot.

However, the extracted feature matrices contain lots of intra-class variations. On the other hand, there exists low inter-class variations among such feature matrices extracted from various traffic video shots of different classes. To capture the intraclass variations as well as representing traffic video shots of different classes effectively, an interval valued feature vector representation is formulated to represent each traffic video shot. Traffic video shots are then classified based on symbolic similarity measure.

#### **2.1 Pre-processing**

Given a frame sequence of a traffic video shot, the pre-processing step is done to segment the content of the frames by their texture. A Gabor filter [8] with different frequencies along with predefined orientations is applied on the RGB channels of each of the frames of a traffic video shot. Each of these filters gives an image as a two-dimensional array of the same size as the input frame. The magnitude of each of the Gabor filtered images is taken and added to each other to get a final filtered image for a given frame. The obtained filtered image is then mapped on the given frame to segment its texture content. The margin of the segmented frame is then cropped to have only the content of the frame.

The above mentioned pre-processing step is employed to segment the content of the frame sequences of traffic video shots. The segmented texture content of the sample frames of three different traffic video shots are shown in Fig. 1.



**Fig. 1.** Frame segmentation of traffic video shots. (a) Sample frames of light, medium, and heavy traffic, (b) Final Gabor filtered images of the frames, (c) Segmented texture content of the frames after mapping the filtered images on the sample frames and cropped the margin of the segmented frames.

#### **2.2 Symbolic Feature Representation**

To gather the statistical data on a traffic activity, the content of traffic video shots can be represented by motion. However, the motion of traffic video shots has a limited ability to distinguish between heavy traffic (almoststopped traffic) and lighttraffic(almost empty/stationary roadway). The estimated motion of such traffics is nearly the same. Moreover, the estimated motion of heavy traffic with slight speed cannot be well classified from the medium traffic at reduced speed.

Therefore, we propose to represent the content of a traffic video shot by appearance and texture in addition to motion. Hence, motion, appearance, and texture features of the content of traffic video shots are extracted.

#### **Features Based on Motion**

Motion estimation is the process of determining motion vectors that describe the transformation from one 2D image to another. We propose to estimate the motion of a traffic video shot using a global pixel-based method by considering the whole frame as one block. Sum of absolute differences (SAD) is considered as an evaluation metric to compute the motion of a frame with respect to its previous one.

Let  ${F_1, F_2, F_3, ..., F_R}$  be a set of R frames of a traffic video shot. Considering the  $k<sup>th</sup>$  frame, say F<sub>k</sub>, the motion of a frame F<sub>k</sub> with respect to the previous frame F<sub>k-1</sub> is calculated as,

$$
MF_{k} = \sum_{x=1}^{u} \sum_{y=1}^{v} \left| F_{k}(x, y) - F_{k-1}(x, y) \right|
$$
 (1)

where,  $F_k(x,y)$  and  $F_{k-1}(x,y)$  are the intensity values of the pixels at  $(x,y)$  of the frames  $F_k$  and  $F_{k-1}$  respectively. Also, u and v define the size of the frames.

Therefore, a column vector called motion feature vectorsay MFof size R-1, considering the adjacent frames, is obtained.

In order to have a compact representation of the obtained motion feature vector in addition to capturing the variations of the motion feature values, we propose to represent the motion feature vector in the form of an interval valued feature vector. Though, it shall be noted that motion is a dominant feature for content representation of a traffic video shot.

Hence, we propose to symbolically represent the motion feature vector by preserving the variations of the features as well as conserving the domain of the features. So, we end up having an interval valued feature vector of dimension 2 representing motion of a traffic video shot.

An interval valued motion feature preserving the variations among the motion feature values is represented as,

$$
Motion\_Interval1 = \left[ MF^{-}, MF^{+}\right]
$$
 (2)

where,

$$
MF^- = \mu\left(MF\right) - \tau\left(MF\right) \quad \text{and} \quad MF^+ = \mu\left(MF\right) + \tau\left(MF\right) \tag{3}
$$

where,  $\mu(MF)$  is the mean of the motion feature values,  $\sigma(MF)$  is the standard deviation of the motion feature values, and  $\tau(MF)$  is the function of  $\sigma(MF)$ given by  $\tau(MF)$  $= \alpha \times \tau(MF)$  for some scalar value  $\alpha$  that is set empirically.

Similarly, another interval valued motion feature capable of conserving the domain of the motion feature values is obtained as,

$$
Motion\_Interval\ 2 = \left[ MF^{-}, MF^{+}\right]
$$
 (4)

where,

$$
MF^- = \min(MF) \quad \text{and} \quad MF^+ = \max(MF) \tag{5}
$$

where, min(MF)andmax(MF)are the minimum and maximum of the motion feature values.

Hence, the motion feature vector is symbolically represented by two interval valued features named as Motion\_Interval1 and Motion\_Interval2.

#### **Features Based on Appearance**

To represent the distribution of the data values in a traffic video shot, a histogram of each of the frame is extracted. Considering the  $k<sup>th</sup>$  frameF<sub>k</sub>, the RGB histograms of the frame  $F_k$  are represented by  $H$  number of gray levels, in here 256 gray levels, as the number of bins. The represented color channel histograms are assimilated and represented as a single appearance distribution vector for the frame  $F_k$  by considering the maximum frequency of the color channels.

A matrix called appearance feature matrix, say AFof size  $R \times \mathcal{H}$  (here  $R \times 256$ ), is obtained. Each row is an appearance distribution vector representing its respective frame.

Instead of keeping this huge feature matrix, we recommend capturing the variation of the entire matrix in the form of an interval valued. Thus, we end up having an interval valued feature representing the appearance of a traffic video shotgiven by,

$$
Appearance\_Interval = \left[ AF^{-}, AF^{+} \right] \tag{6}
$$

where,  $AF$ <sup>-</sup> and  $AF$ <sup>+</sup> are the limits of the interval computed as in Equation (3).

Hence, the appearance feature matrix is symbolically represented by an interval valued feature called Appearance\_Interval.

#### **Features Based on Texture**

A statistical method of examining textures that consider the spatial relationship of pixels is the gray level co-occurrence matrix (GLCM), also known as the gray level spatial dependence matrix. The GLCM matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. The GLCM function calculates how often a pair of pixels with specific intensity (gray level) values and in a specified spatial relationship occur in an image [9].

We use a GLCM functionwhich creates multiple GLCMs for a single input frame. Thus, an array of offsets for the GLCM function is identified. These offsets define pixel relationships of varying directions and distances. After generating the GLCMs, four statistical textural features [9] such as contrast, correlation, energy, and homogeneity are derived.

Considering the k<sup>th</sup> frameF<sub>k</sub>, the four GLCMs of the frame F<sub>k</sub> are obtained by defining an array of offsets specifying four directions  $(0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ})$  with distance 1. For each of the obtained GLCMs, the statistical textural features such as contrast, correlation, energy, and homogeneity are calculated. In addition to these statistical textural features, the entropy of the frame  $F_k$  is also estimated as an added feature, thereby totally 17 features.

In general, T number of statistical texture features are extracted for the frame  $F_k$ . So, a texture vector of size T is created (here  $T=17$ ). Furthermore, it has to be noticed that all the 17 statistical texture features are of different nature.

A matrix called texture feature matrix, say TFof size  $R \times \mathcal{T}$  (here  $R \times 17$ ), is obtained.

To compress the representation of this matrix and to capture the variations of the extracted features, we recommend capturing the variations in each column in the form of an interval valued. Thus, we end up having 17 interval valued features given by,

$$
Texture\_Interval\_Vecor = [TF_1, TF_2, ..., TF_{17}]
$$
\n(7)

where, each TF<sub>i</sub>,  $i = 1, 2, ..., 17$ , is an interval valued feature computed as in Equation (3) for the respective column of TF.

#### **2.3 Traffic Video Shots Representation and Classification**

We propose to represent the traffic video shots in the knowledgebase by their reference feature vectors. The reference feature vectors are represented by assimilating the obtained interval valued features discussed in subsection 2.2. The reference feature vectors are used in classification.

Given a test sample traffic video shot, its similarity values with respect to all the reference feature vectors stored in the knowledgebase are computed. The test sample traffic video shot is then labeled by the class label of a traffic video shot with a maximum similarity.

#### **Representation**

Let there be O number of traffic video shots to be represented in the knowledgebase. A traffic video shot, say  $T_i$  (j =1, 2, 3, ..., O), is represented by a reference feature vector, say Ref<sub>i</sub>given by,

$$
Ref_j = (Motion\_Interval 1, Motion\_Interval 2, Appearance\_Interval, Texture\_Interval\_Vector)
$$
 (8)

Hence, a vector of interval valued features of dimension 20 is formed. Similarly, each traffic video shot is represented by its reference feature vector. Thus, O number of reference feature vectors are created and stored in the knowledgebase.

#### **Classification**

We propose to compute the similarity of a given test sample traffic video shot, say  $T_t$ , with respect to all the reference feature vectors stored in the knowledgebase by the use of symbolic similarity measure [6]. The similarity is estimated between the feature vector of a test sample and the reference feature vectors stored in the knowledgebase.

Thus, it is proposed to represent a test sample traffic video shot  $T<sub>t</sub>$  by a crisp feature vector, say VF.

$$
VF = (Motion_mean, Motion_mean, Appearance_mean, Terxture_mean\_Vector)
$$
 (9)