Traffic Control and Monitoring Based upon Density Estimation in Various Traffic Condition using Artificial Intelligence

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Abstract— In this survey paper the design and development of an application that aims to detect and estimate the number of vehicle are presented on road, in order to maximize traffic light functioning. First, a selection process of interest region is applied to the image sequences, multiplying a mask image with the original image to focus the segmentation in this region. Then, it is segmented by an iterative algorithm, which estimates the background to offset the light intensity variation; it extracts the objects on the road and, through morphological processing, removes the small lines and shapes. Now, object detection, tracking and classification of objects are done. The Objects are detected using optical flow method and traced using kalman filtering method. The objects extracted are classified using ten features including shape based features such as area, height, width, compactness factor, elongation factor, skewness, perimeter, orientation, aspect ratio and extend. A comparative analysis is presented in this paper for the classification of objects (car, truck, auto, human, motorcycle, none) based on Multi-class SVM (one vs. all), Back-propagation, and Adaptive Hierarchical Multi-class SVM (Support Vector Machine).

Key words: Object classification, Object detection, Object tracking, Digital Image Processing, Feature Extraction

I. INTRODUCTION

The steady population growth has generated increased demand for transportation, road traffic and vehicle fleet. This increase arises due to: an increase in purchasing power by the middle class society, the increase in coverage of bank credits, reducing the sales prices of particular cars, the growing supply of used cars and the lack of structured policies in urban transportation. This increase causes more congestion, accidents and environmental problems. Detecting and recognizing moving vehicles in traffic scenes for traffic surveillance, traffic control, and road traffic information systems is an emerging research area for Intelligent Transportation Systems. Today, projects that maximize the control of traffic using different methods have been developed. Reference [3] does the treatment of the images according to light intensity and estimates the vehicles' velocity approaching the intersection road.

The proposed system is a smart surveillance system which works for both real time and prerecorded traffic videos. The combination of methods used is unique, with suitable approach at each step. In case of prerecorded videos, if the videos are large, to save time and resources, shots are detected from it using colour histogram difference method, followed by key frame extraction as described in [4]. For detection of objects, the Optical Flow Model [5] is used. The objects detected in the video are tracked by Kalman Filtering method [6].

II. LITERATURE SURVEY

Background subtraction is a simple approach to detect moving objects in video sequences. To deal with the difficulties arising during background subtraction, several methods have been proposed in [7]. These methods try to detect moving regions taking into account not only the temporal evolution of the pixel intensities and colour but also their spatial properties. After a thorough research, the following algorithms were concluded the best suited for this system. For object detection the Optical Flow Model[4] and Kalman Filtering [6] for tracking objects including in real time.

A comparative analysis of classification algorithms Multi-class SVM (one vs. all), Adaptive Hierarchal Multi-class SVM and Backpropagation is presented for categorizing detected objects. The set of features used to train and the test combination of shape and texture features, namely perimeter, height, width, area, extent, compactness, elongation, orientation, aspect ratio and skewness. the classification algorithms were a unique combination of shape and texture features, namely perimeter, height, width, area, extent, compactness, elongation, orientation, aspect ratio and skewness.

III. METHODOLOGY

A. *Image Capture:*

A video, in the road intersection in the city of Medellin is captured (CL 33 with CR 51 from the Metro station "Exposiciones") with a Samsung ES65 camera of 10.2 Megapixels and spatial resolution of 640 x 480 at 30 $f/$ sec. This video is subject to digital image processing through the platform of Visual Studio 2008 C++, supplemented with OpenCV libraries.

B. *Selection of Interest area:*

Manually, the region of interest is selected; generating animage mask, Bmn. Using (1), Bmn is multiplied with Amn,original image, in order to focus segmentation on the interest region. Also manually, the contour of a vehicle is traced to determine, based on the location of the camera, the approximate area, AV, of these, as shown in Fig 1. The selection of the above regions, are made by the user installing the camera.

$$C_{mn} = A_{mn} * B_{mn}$$
$$= \begin{bmatrix} A_{11}.* B_{11}, A_{12}.* B_{12} & \cdots & A_{1n}.* B_{1n} \\ \vdots & \ddots & \vdots \\ A_{n1}.* B_{n1}, A_{n1}.* B_{n1} & \cdots & A_{nn}.* B_{nn} \end{bmatrix} \quad (1)$$

C. Segmentation:

This process is made approximately every 10 minutes due to the constant changes of light intensity in the environment, at the time that occupancy of the track is below to 5%, this in order to obtain an image histogram similar to the Gaussian function. Fig. 3 clearly shows two moments in the day where the light intensity in the environment has changed considerably, therefore the range [P1, P2] has also changed.

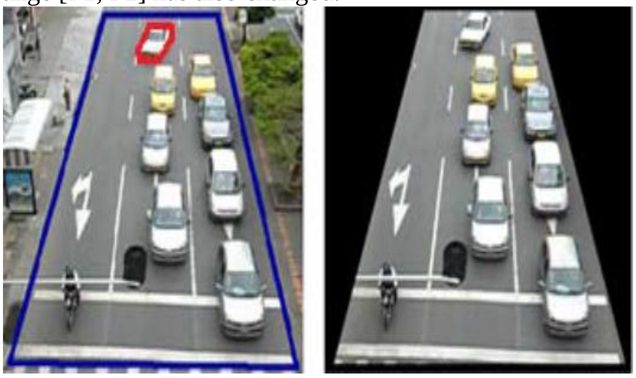

Fig. 1: selecting region of interest

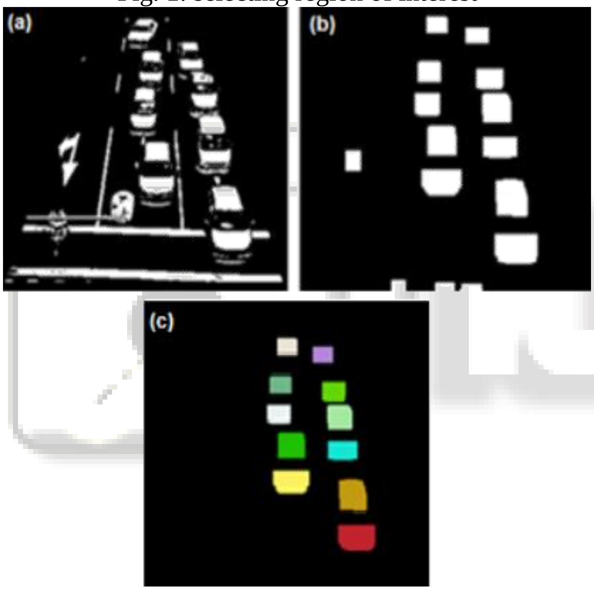

Fig. 2: (a) background estimation, (b) morphological processing and (c) selection of contour

D. Analysis:

With the addition of the areas, Sa, of the resulting objects, that is to say vehicles, the percentage, Pn, of these with respect to the total area of the interest region, Ar, previously selected, is calculated. Thus determining experimentally, the road occupancy level, which is estimated between 2% and 25%, the latter being the maximum occupancy level.

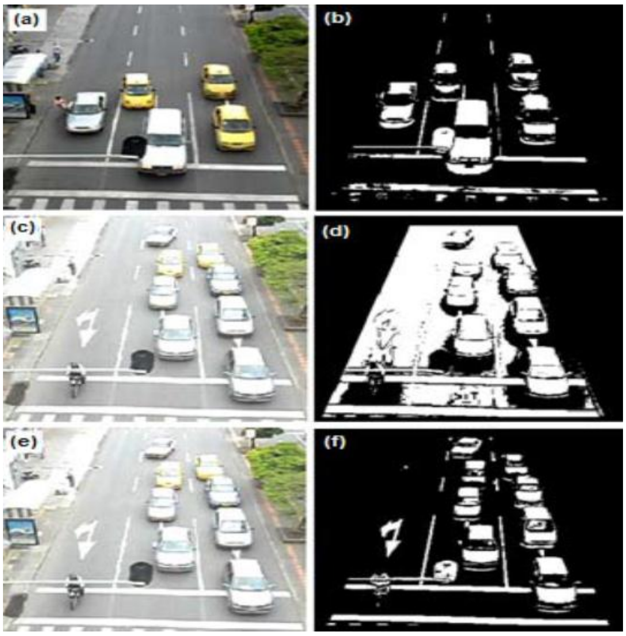

Fig. 3: Filtering with light intensity variation

IV. OBJECT DETECTION USING OPTICAL FLOW MODEL

Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image. Discontinuities in the optical flow can help in the segmentation of images into regions that correspond to different objects [4]. Median filtering is applied to remove speckle noise, using a velocity threshold obtained from Optical flow method. Morphological operations are done to remove small objects and holes.

V. KALMAN FILTERING FOR OBJECT TRACKING

The Kalman filter [6] tracking algorithm is used to track multiple objects. Thus, the position estimate in the next frame is determined. Then, the weights are updated; when the position in the next frame is known (it becomes present frame). Higher weights are given to those object tracks with higher certainty of being to that track and vice versa. The predicted tracks are The Adaptive Hierarchical Multi-class SVM method in [8] using a top-down approach for training and testing. This has been implemented which used a decision tree approach. The dataset is divided into two non-overlapping subsets using k-means clustering algorithm (k=2). The means of each class is the input to the clustering algorithm.

Using SVM, which is a binary classification algorithm, it is trained with one cluster given as positive samples and the other as negative sample. This is continued for each cluster till only one class remains. For testing purpose, a decision binary tree is built and a top-down approach is used. Starting from the root node, it goes down left or right sub-tree until it reaches a leaf which is the class it belongs to. This tree classifier for has 5 internal SVM nodes. The kernel function used is the Gaussian Radial Basis Function for both described above. The Levenberg-Marquardt Back-propagation Method is also used for classification. The number of input nodes is 10 which the number of features, number of hidden layer nodes is 12 and number of output nodes is 6. The number of patterns used is 1016 and learning rate used is 0.01.

VI. EXPERIMENTAL ANALYSIS AND RESULTS

A training set of 1016 samples was prepared using 13 different videos, having a combined duration of 12 minutes and 20880 frames in total. Similarly, a testing set of 500 samples was created using 4 different videos, having a combined duration of 4 minutes and 6960 frames in total. As shown below in table 4, Multi-class SVM has highest accuracy so its trained classifier is used to classify objects in real time with the count determined for each type of object as shown in Fig 2. The objects (vehicles and human) which are indexed and stored can be queried using type, dimension and/or color, depending on the object type.

A. Confusion Matrix:

Confusion Matrices for classification algorithm are shown in Table 1, 2 and 3. Efficiency of all three algorithm is shown in Table 4.

Predicted class → Actual ↓ Class	**CAR**	**BIKE**	**BUS/TRUCK**	**HUMAN**	**AUTO**	**JUNK**
CAR	199	2	1	1	0	22
BIKE	4	86	0	0	0	5
BUS/TRUCK	0	0	15	0	1	1
HUMAN	0	0	0	10	0	1
AUTO	0	0	0	0	2	0
JUNK	3	0	0	0	0	148

Table 1: Confusion Matrix for Multi class SVM[2]

Predicted class → Actual ↓ Class	**CAR**	**BIKE**	**BUS/TRUCK**	**HUMAN**	**AUTO**	**JUNK**
CAR	171	0	0	1	0	12
BIKE	3	82	0	0	0	1
BUS/TRUCK	5	0	13	0	0	0
HUMAN	0	3	0	9	0	1
AUTO	5	0	3	0	3	1
JUNK	22	3	0	1	0	161

Table 2: Confusion Matrix for Adaptive Hierarchal SVM[2]

Predicted class → Actual ↓ Class	**CAR**	**BIKE**	**BUS/TRUCK**	**HUMAN**	**AUTO**	**JUNK**
CAR	178	7	5	1	0	28
BIKE	7	75	0	2	0	1
BUS/TRUCK	2	0	10	0	3	2
HUMAN	0	0	0	3	0	0
AUTO	0	0	0	0	0	0
JUNK	19	6	1	5	0	145

Table 3: Confusion Matrix for Back Propagation[2]

B. Accuracy:

Accuracy is the overall correctness of the model and is calculated as the sum of correct classifications divided by the total number of classifications. It is shown in Table 4.

Sr. No	**Classification Algorithm**	**Accuracy**	**Percentage**
1	Multi-class SVM (one vs. all)	460/500	92%
2	Adaptive Hierarchal Multi-class SVM	439/500	87.80%
3	Back-propagation	410/500	82.20%

Table 4: Accuracy of classification Algorithm

C. Precision:

Precision is a measure of the accuracy provided that a specific class has been predicted. It is defined by equation (2), where tp and fp are the numbers of true positive and false positive predictions for the considered class.

$$\text{Precision} = t_p/(t_p+f_p) \qquad (2)$$

	Multi-class SVM (one vs. all)	**Adaptive Hierarchal Multi-class SVM**	**Back-propagation**
$\text{Precision}_{\text{Cars}}$	96.60%	83.00%	86.40%
$\text{Precision}_{\text{Bike}}$	97.72%	93.18%	85.22%
$\text{Precision}_{\text{Truck}}$	93.75%	81.25%	60.25%
$\text{Precision}_{\text{Human}}$	90.90%	81.81%	27.27%
$\text{Precision}_{\text{Auto}}$	66.66%	100%	0%
$\text{Precision}_{\text{Junk}}$	84.90%	91.47%	82.38%

Table 5: Precision of classified objects

VII. CONCLUSION

In this project, a traffic light flow control was developed, through the vehicle count on the road intersection. An adaptive segmentation was used based on the histogram of the images, contours' detection, geometric patterns calculation and the vehicle's area addition, in order to determine the road occupation level.

Objects detected are tracked, and suitable features are extracted for object classification. A comparative analysis of three algorithms, namely Multi-class SVM (one vs. all), Back-propagation, and Adaptive Hierarchical Multi-class SVM is presented, since they are essential to extract suitable vehicle features and vehicle parameters that can be used for object classification. The accuracy was highest for Multi-SVM, 92%, followed by Adaptive Hierarchal Multi-SVM with 88% and then the Back propagation Algorithm, 82%. Classification of objects is done in real time providing the count for each type of object.

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