EE58J Term Project Presentation on: Efficient Feature Extraction for Highway Traffic Density Classification

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Introduction

* This project is the implementation of the article ***'Efficient Feature Extraction for Highway Traffic Density Classification'*** by Mina Abasi Dinani, Parvin Ahmadi, Iman Gholampour published in 9th Iranian Conference on Machine Vision and Image Processing, November 18-19,2015.

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1.Abstract

In this project,we estimate the traffic flow density based on classification. Various new efficient features introduced in the article are used for distinguishing between different traffic states. These features describe the traffic flow without any need to individual vehicles detection and tracking. In this project SVM classifier is used.

2.Dataset

Total # of videos	254
Total # of frames	13063
Clear	51
Rainy	125
Overcast	78

Washington State Department of Transportation

Statistical Visual Computing Lab

UC San Diego

	set #1	set #2	set #3	set #4
# of training videos	191	190	190	191
# of testing videos	63	64	64	63

Heavy	44
Medium	45
Light	165

3.Overview

- A.Static Features
  - Edge Histogram
  - Texture
  - Number of Keypoints
- B.Dynamic Features
  - Pixel Comparison
  - Edges of Difference Image
  - Discrete Cosine Transform (DCT) coefficients histogram of difference-image
  - Changes of Color Histogram

3.1.Static Features

In the problem of traffic density estimation, the number of vehicles in an area shows the density of the traffic. This property can be described using static features which are first calculated from individual frames and concatenated making a feature vector for each video.

3.1.1.Edge Histogram(1:3)

* Modified MPEG- 7 method of calculating edge histogram gives a good representation for the edges in an image.

Procedure:

1. • Image grey levels are reduced to 128 levels that act as a noise removal procedure.

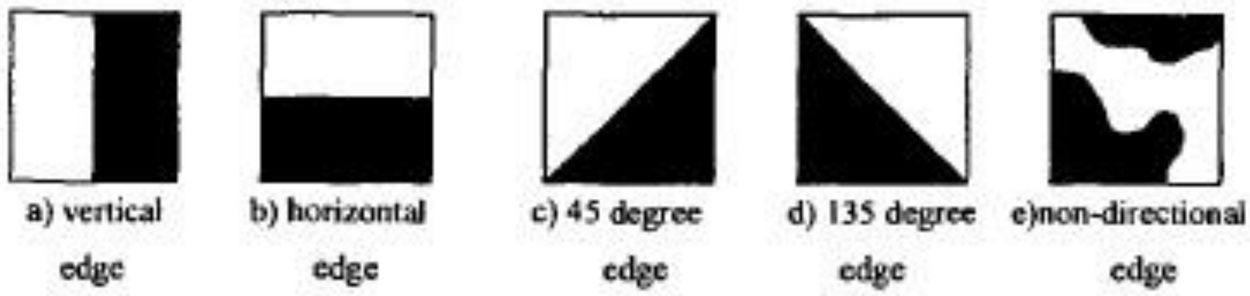
2. • The image is then broken into predefined number of blocks (here 16 blocks).

3. • Blocks are labeled with five edge types of 0, 45, 90, 135 degrees and nondirectional edge.

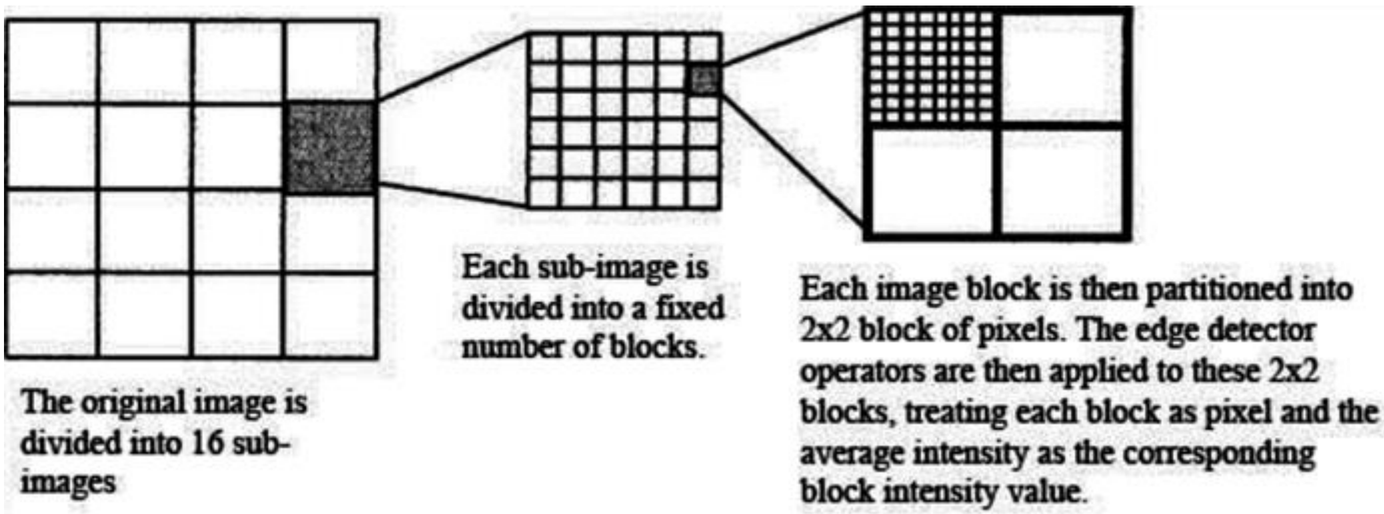
4. • Edge histogram contains 16x5=80 bins.
   • Every bin becomes one element of 80-dimensional edge feature vector.

3.1.1.Edge Histogram(2:3)

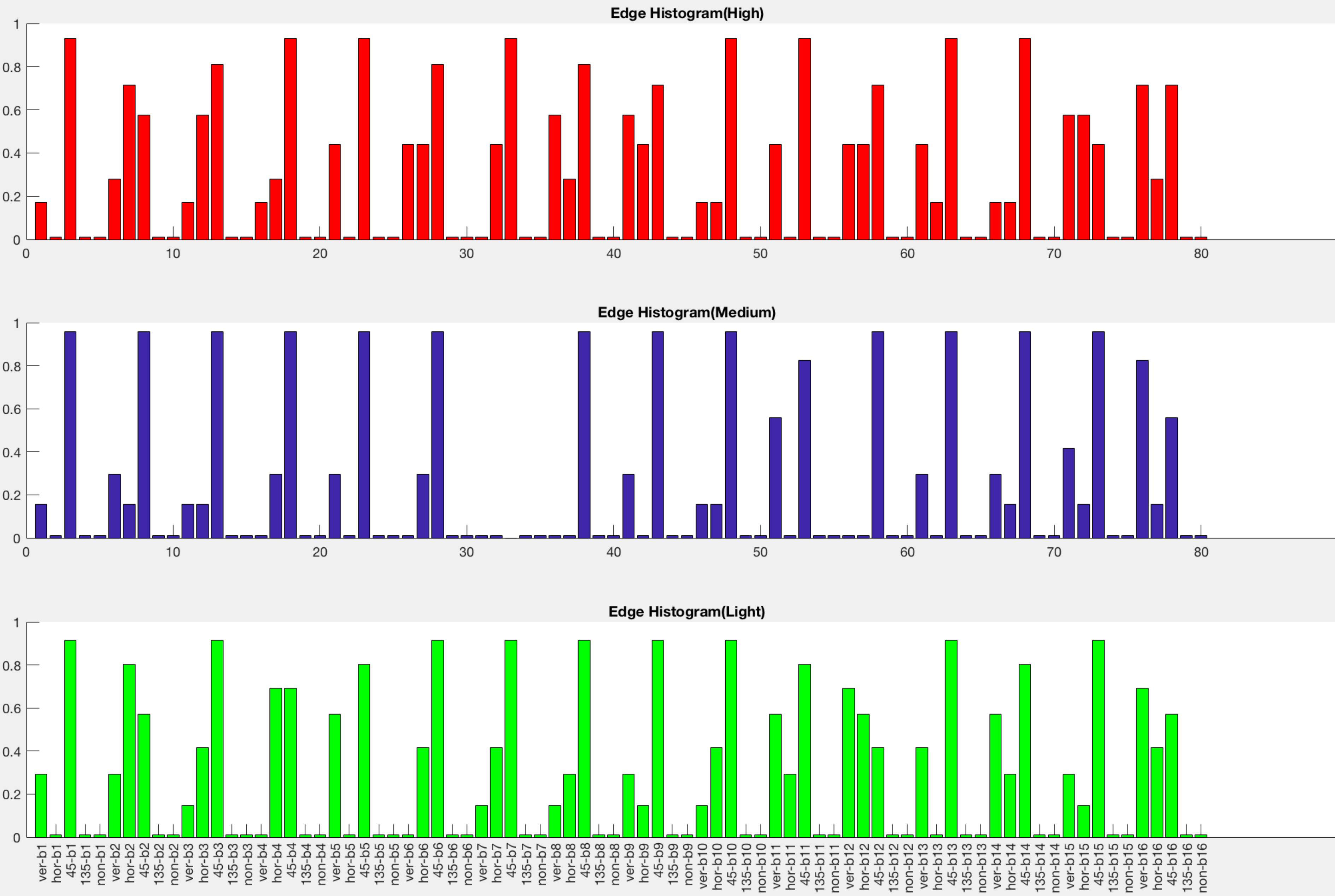
* **MPEG-7 Edge Histogram Descriptor:**



Five types of edges



5.1.1.Edge Histogram(3:3)



3.1.2.Texture(1:2)

To obtain the texture of a scene we calculate the first-order and second-order statistics. With 5 first-order statistics and 4 second-order statistics, an 9-dimensional feature vector is obtained.

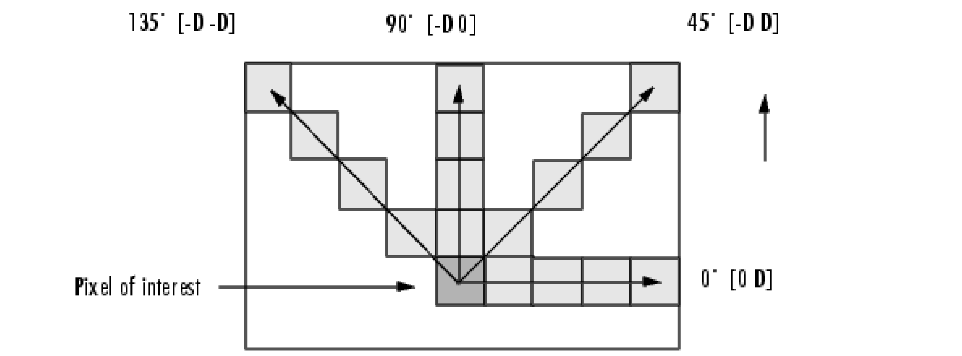
3.1.2.Texture(2:2)

1.

- First-order texture statistics are calculated based on histogram of gray levels.
- These are: overall mean, standard deviation, skew, variance, uniformity, Entropy.

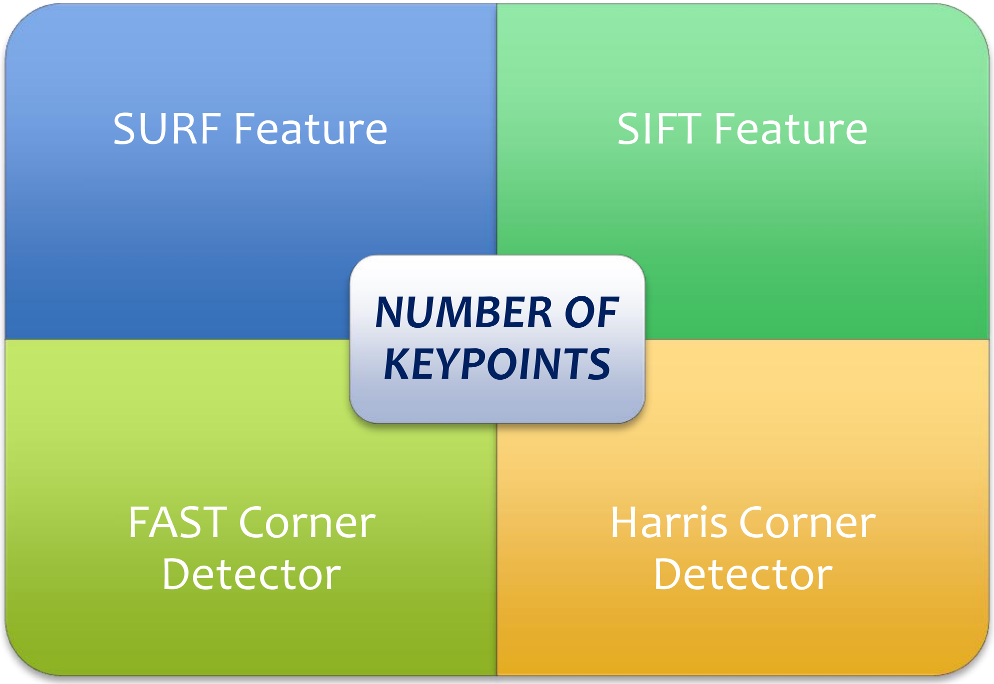
2.

- Second-order statistics are calculated using Gray level Co-Occurrence Matrix (GLCM).
- GLCM is calculated based on position operators. We consider position operators with one pixel length and four different directions: 0, 45, 90, 135 degrees. The symmetric GLCM and its corresponding statistical descriptors are calculated for each frame with each position operator
- The descriptors are: angular second moment (energy), Entropy, contrast and correlation



3.1.3.Number of Key Points(1:5)

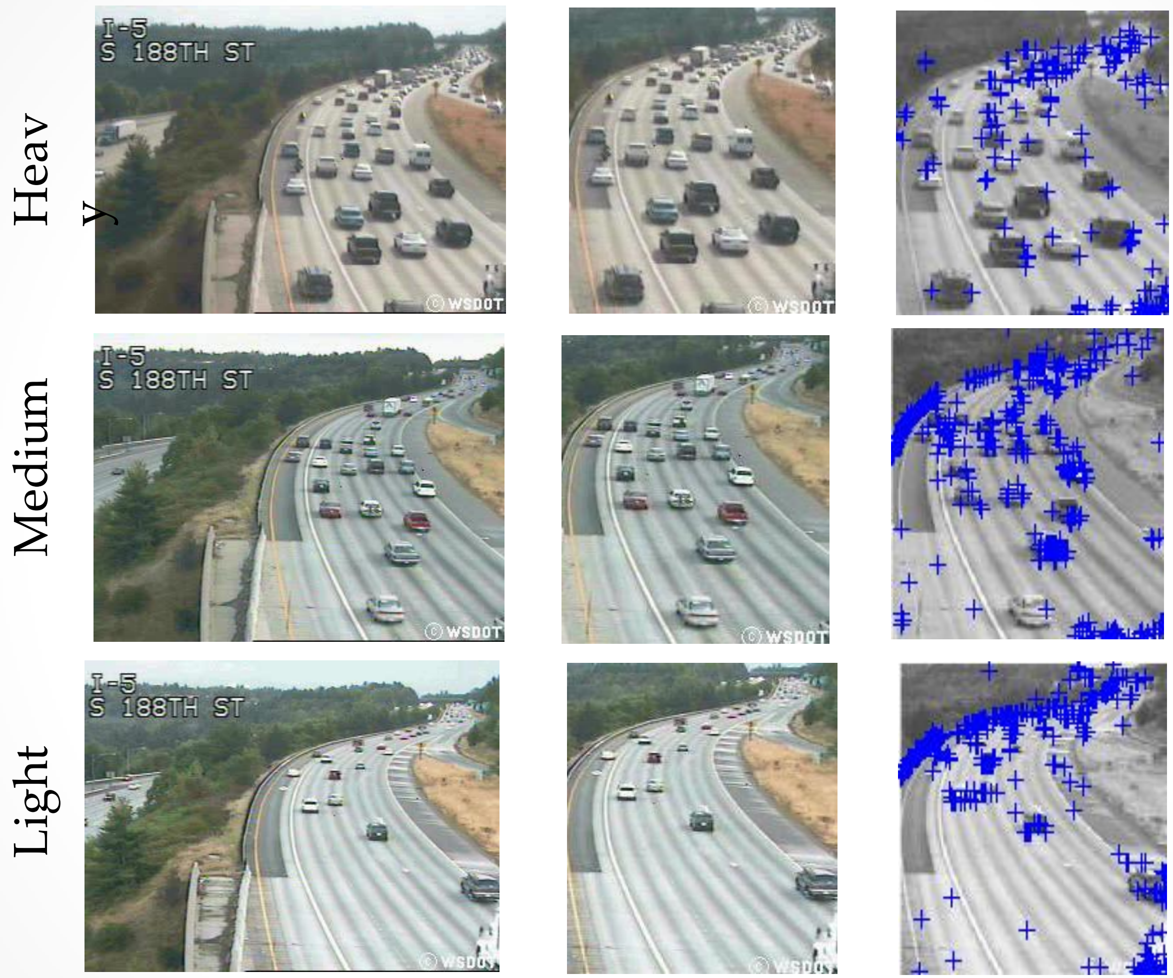
* In these algorithms key-points are selected at distinctive locations such as blobs, corners and T-junctions.
* The image with higher level of details have more corners, T-junctions and blobs.



3.1.3a) SURF Features(2:5)

a)Traffic image   b) ROI   c) detected SURF key-points in ROI

3.1.3b) SIFT Features(3:5)



a)Traffic image

b) ROI

c) detected SIFT key-points in ROI

3.1.3c) FAST Corner Detector(4:5)

Heavy

Medium

Light

a)Traffic image

b) ROI

c) detected FAST corner points in ROI

3.1.3d) Harris Corner Detector(5:5)

Heavy

Medium

Light

a)Traffic image

b) ROI

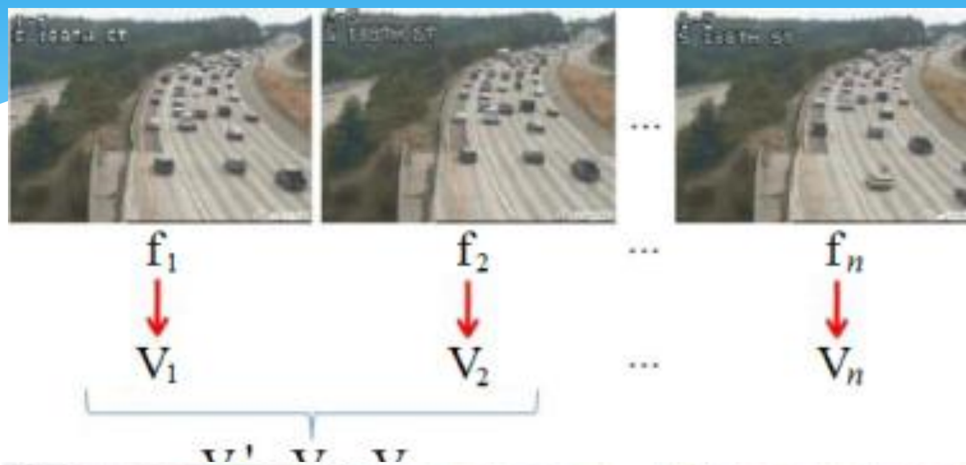
c) detected HARRIS corner points in ROI

3.2.Dynamic Features(1:2)

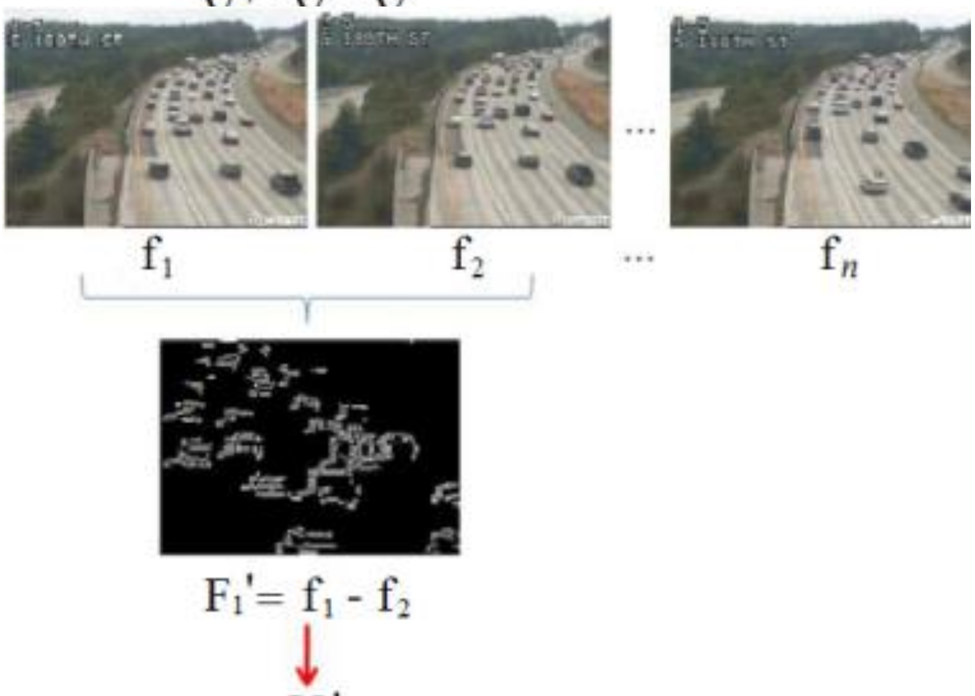
Dynamic features describe the traffic density based on changes of the video scene in a given time duration. Since the level of traffic density affects the speed of vehicles and changes of the scene is directly related to the vehicles speed, the amount of scene changes from one frame to another can define the level of traffic density.

3.2.Dynamic Features(2:2)

Feature Extraction Methods:



f→ frame
V→static feature vector
V'→difference(dynamic) feature vector



f→ frame
F'→difference image
V'→difference image feature vector

3.2.1.Pixel Comparison(1:2)

Comparison of corresponding pixels in successive frames shows the variation of **illumination** in them. Simple comparison of pixels inconsecutive frames cannot differentiate between a big change in a small area of an image and a small change in a big area of that image. One way to obtain a better feature without this drawback is to consider the pixel differences that are more than an experimental threshold.

3.2.1.Pixel Comparison(2:2)

Procedure:

1. Based on Eq. (1), the difference of color or illumination (P) of two corresponding pixel in (x, y) location of frames is computed and compared with threshold T.

2. Based on Eq. (2), differences in all frame pixels that are more than T are added up and normalized by the area of frame (here XY).

$$DP(i, i+1, x, y) = \begin{cases} 1 & \text{if } |P_i(x, y) - P_{i+1}(x, y)| > T \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$D(i, i+1) = \frac{\sum_{x=1}^{X} \sum_{y=1}^{Y} DP(i, i+1, x, y)}{XY} \quad (2)$$

3.2.2.Edges of Difference Image(1:2)

* Canny operator is applied on difference-image based on the equation below, Φ shows the Canny operator.

$$DE_i = \Phi\,(|\,f_{i-1} - f_i\,|)$$

* Edge of difference image depends on two factors:

-number of vehicles in the scene

-vehicles speeds in consecutive frames

3.2.2.Edges of Difference Image(2:2)

- (a) previous frame (b) current fram(c) difference-image and (d) edges of difference

3.2.3. Discrete Cosine Transform (DCT) coefficients histogram of difference-image

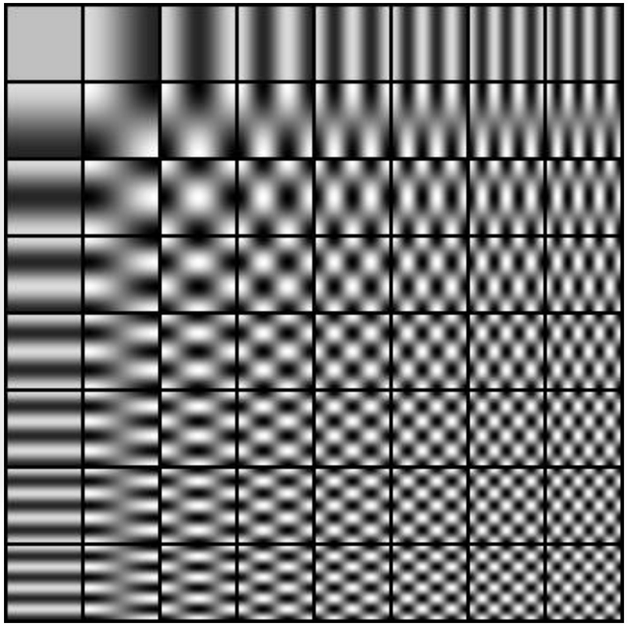
* Discrete cosine transform is a method of transforming a signal to its frequency components.
* For a two dimensional mxn signal s such as an image, discrete cosine transform S is calculated based on :

$$S(u,v) = \frac{2}{\sqrt{nm}} C(u)C(v) \sum_{y=0}^{m-1} \sum_{x=0}^{n-1} s(x,y) \cos\frac{(2x+1)u\pi}{2n} \cos\frac{(2y+1)v\pi}{2m},$$

$$u = 0, \ldots, n, v = 0, \ldots, m$$

Where:

$$C(u) = \begin{cases} 1/\sqrt{2} & u = 0 \\ 1 & otherwise \end{cases}$$



DCT Base Patch

3.2.4.Change of Color Histogram

* Since the color of vehicles are random, color histogram information does not use in many traffic applications.
* Nevertheless, the "changes of color histogram" in consecutive frames of traffic video can be used as a criterion of scene changes.

3.2.4.Change of Color Histogram(1:3)

Procedure:

1.
- 256 dimensional RGB color space is reduced to 64 dimensions and then the color histogram is obtained.

2.
- Bhattacharyya distance is used to calculate changes of color histogram.

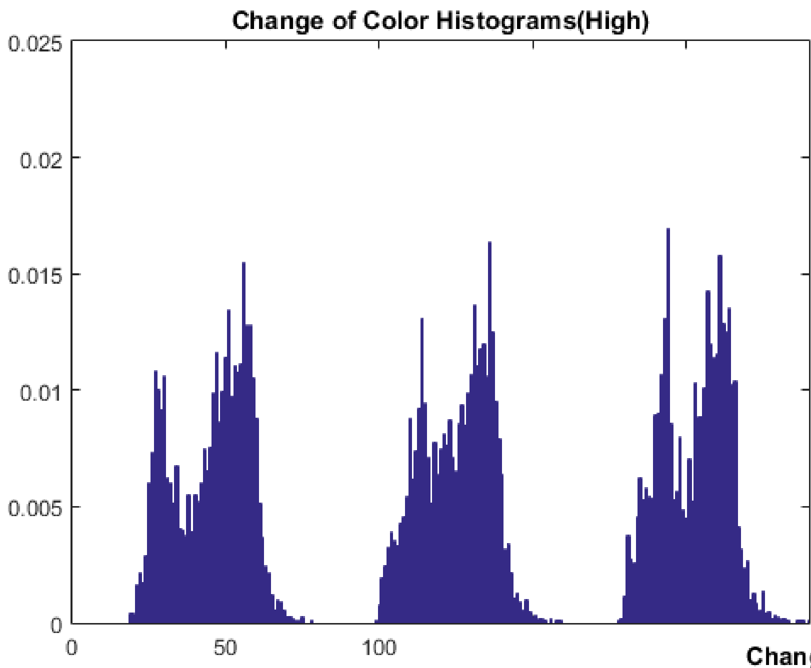
3.2.4.Change of Color Histogram(2:3)

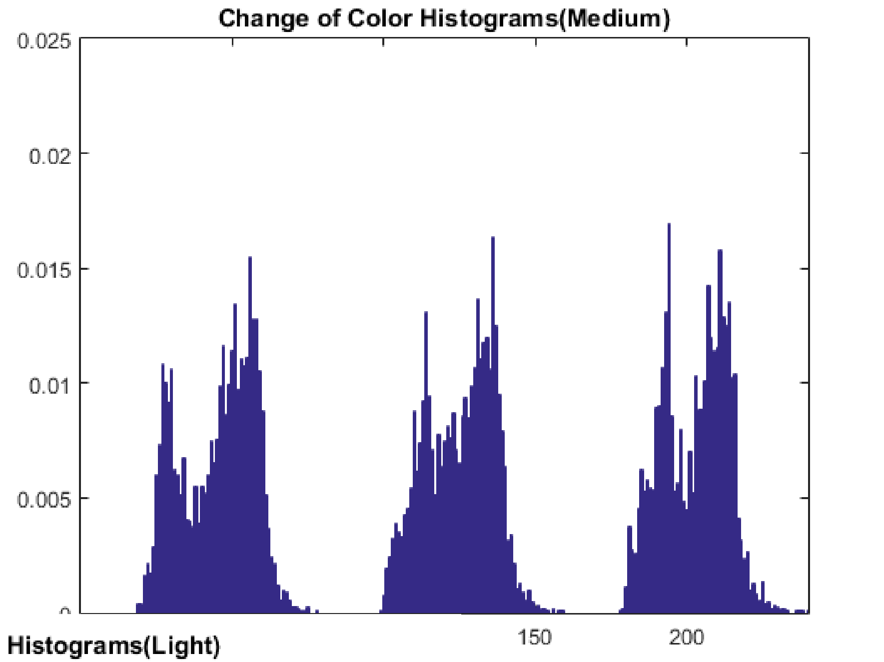
Bhattacharyya distance calculation:

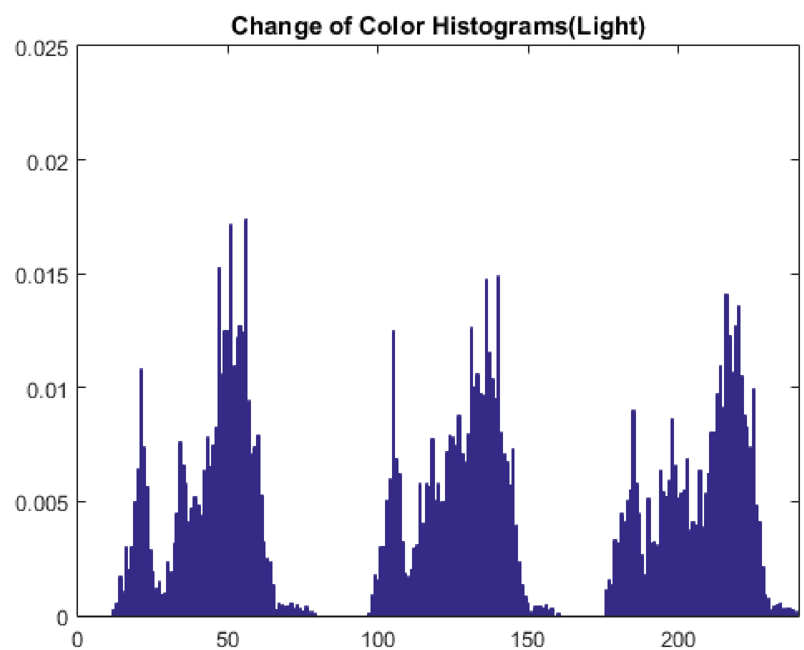
$$d(H_1, H_2) = \sqrt{1 - \frac{1}{\sqrt{H_1 H_2 N^2}} \sum_i \sqrt{H_1(i).H_2(i)}}$$

H1→Histogram of previous frame
H2→Histogram of current frame
N→# of histogram bins

3.2.4.Change of Color Histogram(3:3)







3.3.Combination

* Two different approaches are developed to achieve a final result:

1. All feature sets are combined into one and an SVM model is trained with this new feature set.
2. Two most accurate features(Edge Histogram and SURF features) are combined.

4.Classification Method

* LIBSVM library is used for all feature sets.

* **Kernel type** : Linear
* **Type of SVM:** C-SVC

5.Experimental Results

Results we obtained:

Type	Feature	Classification Accuracy
Static	Edge Histogram	84,82%
	Texture	64,92%
	SIFT	64,95%
	SURF	80,14%
	FAST corner	65,71%
	Harris corner	64,90%
Dynamic	Pixel Comparison	60,67%
	Edges of Difference Image	62,85%
	DCT Coefficients Histogram	64,95%
	Changes of Color Histogram	64,95%

All Features	65,20%
SURF and Edge Histogram	85,71%

Results in the article:

Type	Feature	Classification Accuracy (%)
Static	Edge histogram	79.3
	Texture	71.4
	Number of key-points	82.7
Dynamic	Pixel Comparison	65.6
	Edges of difference-image	82.7
	Moving edges	68.9
	DCT coefficients histogram of difference-image	82.7
	Changes of color histogram	58.6

6.Conclusion

Predicted Class / Actual Class	Heavy	Medium	Light
Heavy	8	3	0
Medium	0	5	6
Light	0	0	41

Sensitivity	73,30%
Specificity	100,00%
Prevalence	17,50%
Positive Predicted Value	100,00%
Negative Predicted Value	94,50%