Pedestrian Detection By Light Detection And Ranging Sensor(LiDAR) in Autonomous Driving System

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3. Semester

Outline

- Motivation
- State of the Art
- Principle
- Application in Autonomous driving
- Limitation of LiDAR
- Conclusion

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Motivation

Two Questions:

Why we need Autonomous Driving ?

Why we need LiDAR?

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State of the Art

- Classification Methods
  - Nearest Neighbor Classifier
  - Approximate Nearest Neighbor (KNN)
  - Spatial Pyramid Matching
  - Histogram of Gradients (HoG)

- Nowadays

  Convolutional Neural Network (CNN)

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Principle

- Linear Classification
- Loss Function
- Optimization
- Backpropagation

Principle

Linear Classification:

$$f(x_i, W, b) = Wx_i + b \qquad (1)$$

[32*32*3] [3072*10] [10*1]

Input:

Xi: the image, in the form of an array

W: the parameter for each pixel in the image, in matrix

b: the bias to correct the classification result

Output:

f: array of labels, which are the scores of each class

Principle

Input

Figure 1:
Pedestrian image[3]

$$f(x_i, W, b) = W x_i + b$$

Output

-3.45
-8.87
0.09
2.9
4.48
8.02
3.78
1.06
-0.36
-0.72

Loss Function

Multiclass SVM loss function:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1) \qquad (2)$$

s_{y_i} : the score for the correct label

s_j : score for other labels

$s_{y_i} \rightarrow$ **3.2**

$s_j \rightarrow$ 5.1

$s_j \rightarrow$ -1.7

Loss : 2.9

Principle

Drawback with Multiclass SVM loss function:

- If the loss is 0, increase the weights for each by n times, the result will still be the same
- Add a regularization at the end

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1) + \mathbf{R} \qquad (3)$$

Principle

Optimization

Linear Classification → Score

Loss Function → Error

To optimize the error:

- Apply the gradient descent algorithm from machine learning to update the parameter to achieve the minimal Error and get the weight W.

$$\Delta \mathbf{w} = -\eta \cdot \frac{\partial \mathcal{L}(\mathbf{w}, b)}{\partial \mathbf{w}} \tag{4}$$

- Using SGC (Stochastic Gradient Descent) to reduce computation

Principle

Backpropagation:

Instead of one single score function, now multiple layers

$$\boxed{f(x_i, W, b) = Wx_i + b}$$

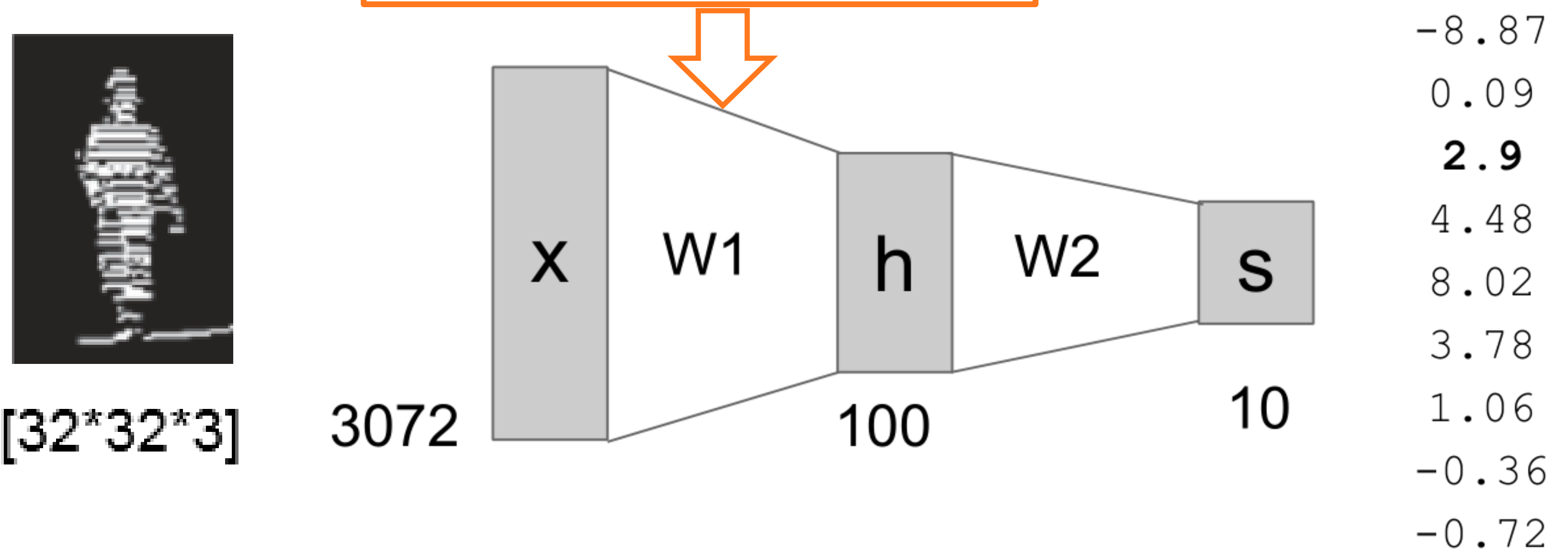

Figure 2:
Multilayer Perceptron[7]

Principle

Backpropagation:

For the optimization for all the neural networks, backpropagation is used to update the gradient of the hidden layers (5)

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x} \tag{5}$$

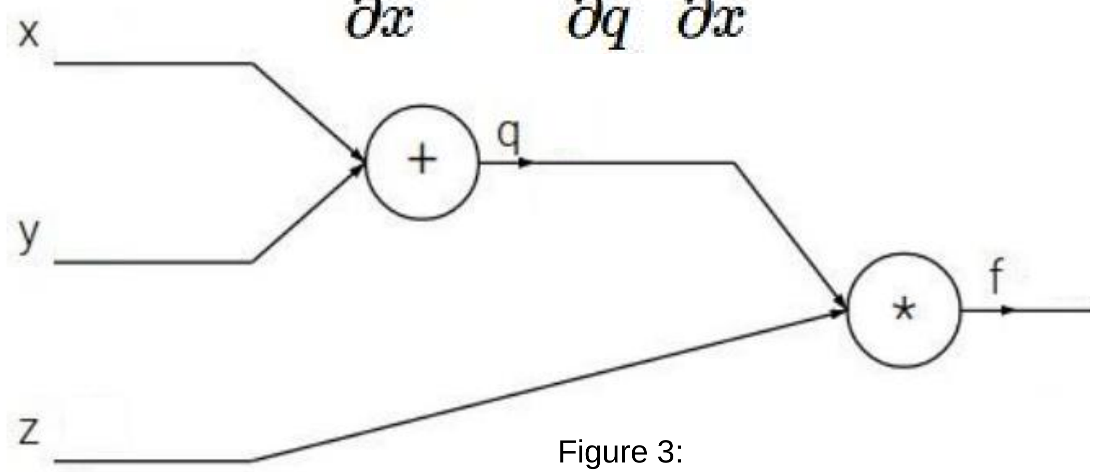

Figure 3:
Backpropagation Chain Rule[7]

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Application in Autonomous driving

- Detect the pedestrians
- Tracking moving pedestrians
- Avoid pedestrians in the path planning
- Parameters in decision making

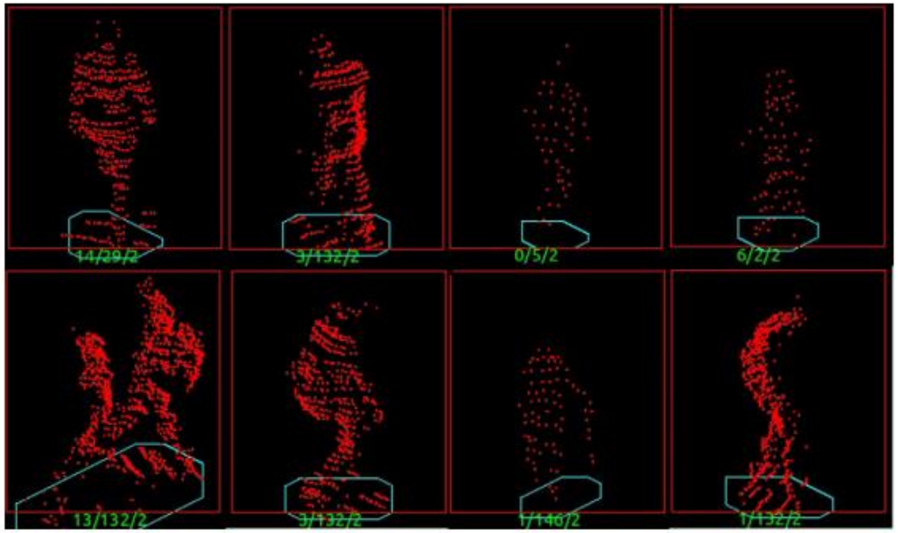

Figure 4: Pedestrian cluster [4]

Application in Autonomous driving

Problems:

The recognition rate is 85% according to this paper,[4] which is not as good as the result by using computer vison on cameras.

Solutions:

Calibration with the help of cameras. [5]

By calibration, the result is improved and also can be used as a redundancy system for the autonomous driving vehicles.

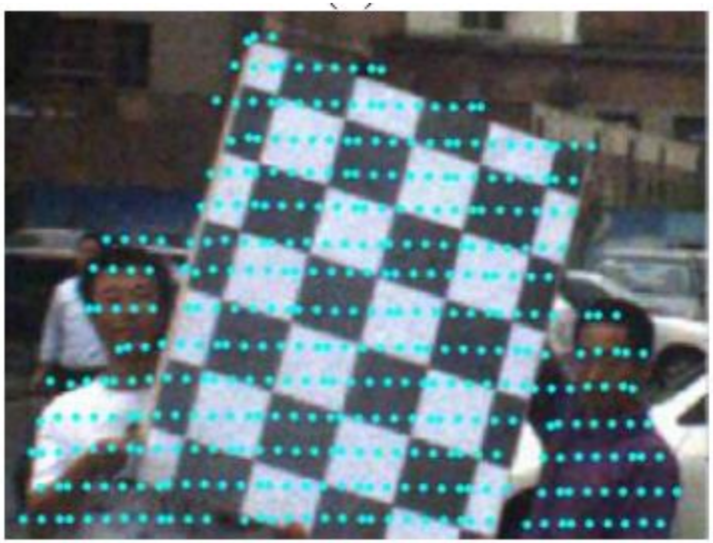

Figure 5: Calibration with the help of cameras[5]

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Limitation of LiDAR

1 Affected by environment

- Can be blocked by flog, snow, and dust
- light maybe reflect from the rain rather than the object

2 can not detect transparent object

- Light will go though the window, and detect the wrong target

3 Extremely high cost

- 7500$ for 1 64-line LiDAR

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Conclusion

Advantage:

- Higher resolution
- Farther detecting distance

Disadvantage:

- Sensible to environment
- Too expensive

Can cooperate well with other sensors, like cameras to ensure the redundancy and reliability

Reference

- Chris Urmson: How a driverless car sees the road
- J. K. Kim, J. W. Kim, J. H. Kim, T. H. Jung, Y. J. Park, Y. H. Ko, and S. Jung, "Study on Extracting Curb Using a LiDAR Sensor", JCROS DaeJeon-Chungchung Regional Conference, pp.161-162,2014.
- Clément Mallet ∗ , Frédéric Bretar, Full-waveform topographic lidar: State-of-the-art , ISPRS Journal of Photogrammetry and Remote Sensing 64 (2009) 1–16
- Heng Wang, Bin Wang, Pedestrian recognition and tracking using 3D LiDAR for autonomous vehicle, Robotics and Autonomous Systems 88(2017) 71-78
- K. Kidono, T. Miyasaka, A.W.T. Naito, J. Miura, Pedestrian recognition using high-definition lidar, in: IEEE Intelligent Vehicles Symposium (IV), 2011.
- Lipu Zhou, Zhidong Deng, Extrinsic Calibration of a Camera and a Lidar Based on Decoupling the Rotation from the Translation, 2012 Intelligent Vehicles Symposium Alcalá de Henares, Spain, June 3-7, 2012
- FeiFei-Li, Andreje, cs231n slides, Stanford, 2016

Thank you

Following slides are prepared for the questions which may be asked.

L1 distance: $d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$

test image

56	32	10	18
90	23	128	133
24	26	178	200
2	0	255	220

\-

training image

10	20	24	17
8	10	89	100
12	16	178	170
4	32	233	112

=

pixel-wise absolute value differences

46	12	14	1
82	13	39	33
12	10	0	30
2	32	22	108

$\xrightarrow{\text{add}}$ 456

L1 (Manhattan) distance

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

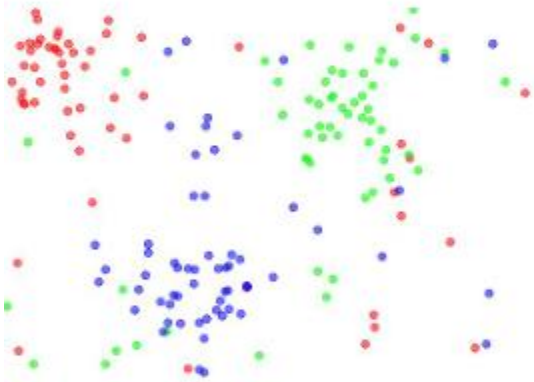
L2 (Euclidean) distance

$$d_2(I_1, I_2) = \sqrt{\sum_p \left(I_1^p - I_2^p\right)^2}$$

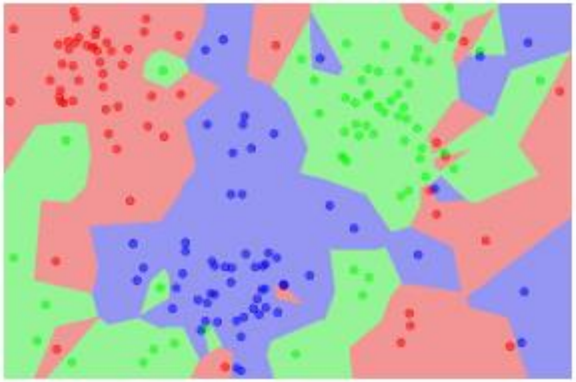
k-Nearest Neighbor

find the k nearest images, have them vote on the label

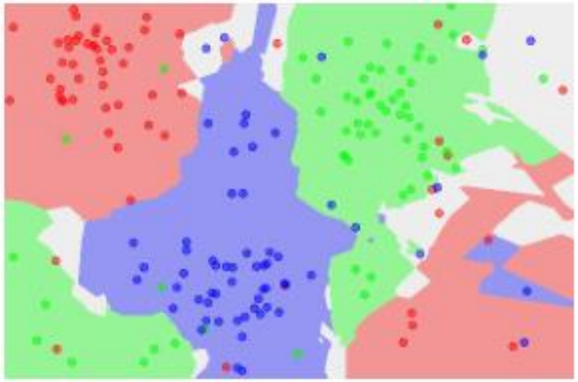
the data

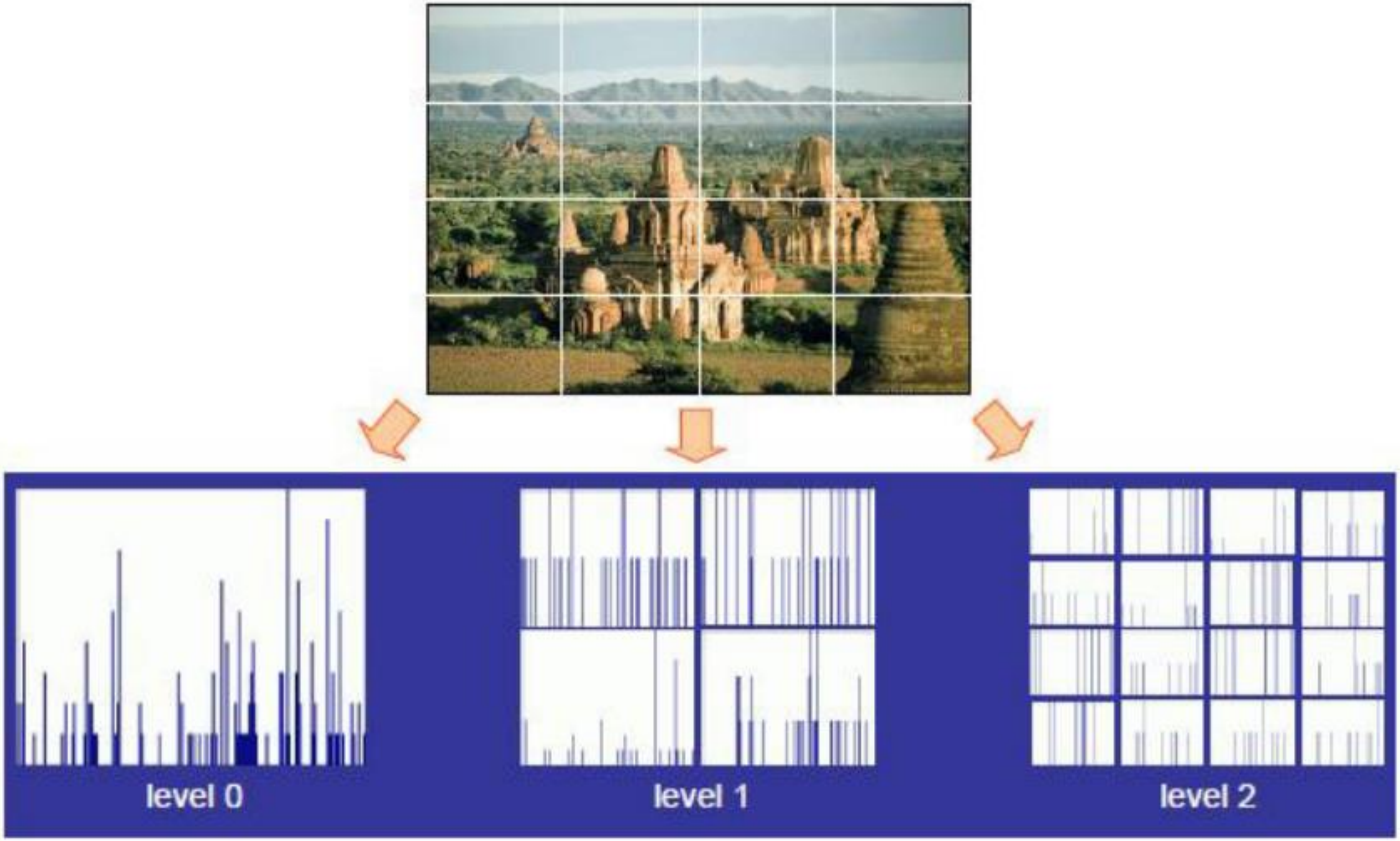


NN classifier

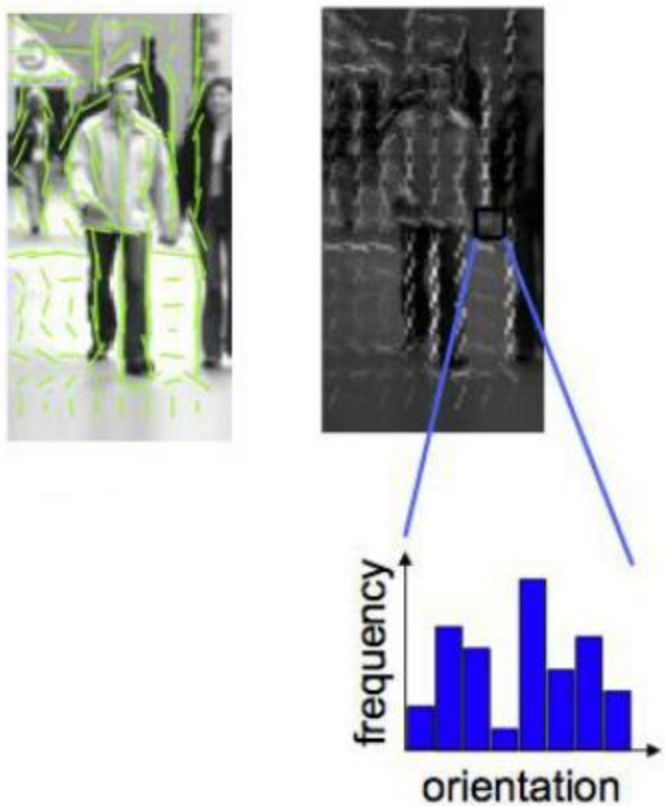


5-NN classifier

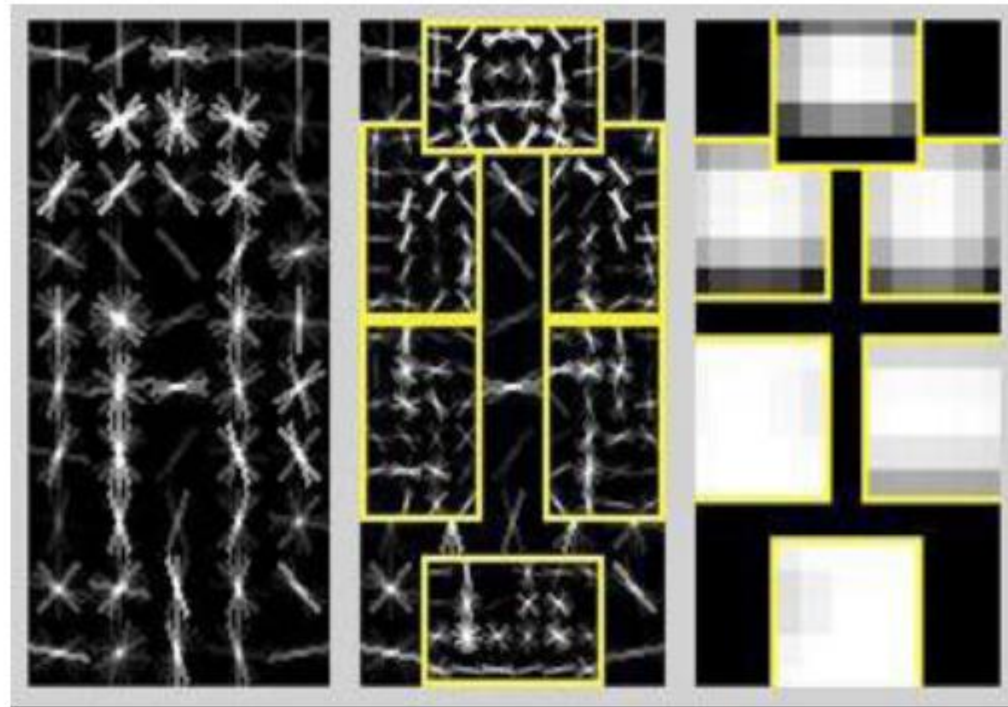




Spatial Pyramid Matching, Lazebnik, Schmid & Ponce, 2006



Histogram of Gradients (HoG)
Dalal & Triggs, 2005



Deformable Part Model
Felzenswalb, McAllester, Ramanan, 2009