



Vidyavardhini's College of Engineering &
Technology

Department of Computer Engineering

Experiment No.9
To Creating and Training an Object Detector
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Aim: To Creating and Training an Object Detector

Objective :Bag of Words (BOW) in computer vision - Detecting cars in a scene

Theory :

Creating and Training an Object Detector

Object detection is a crucial task in computer vision, with applications ranging from autonomous driving to surveillance systems. In this experiment, we aim to create and train an object detector specifically for detecting cars in a given scene. One of the techniques we'll use for this purpose is the Bag of Words (BOW) model.

Bag of Words (BOW) in Computer Vision:

The Bag of Words model, borrowed from natural language processing, has been adapted for use in computer vision. It is a popular image representation technique used for object detection and image classification.

The BOW model works as follows:

1. Feature Extraction: Extract local features, such as SIFT (Scale-Invariant Feature Transform) or ORB (Oriented FAST and Rotated BRIEF), from a set of training images containing the object of interest (in this case, cars).
2. Create a Vocabulary: Cluster the extracted features into a vocabulary of visual words using clustering techniques like K-means. These visual words represent common patterns or features found in the training images.
3. Histogram Representation: For each image, create a histogram that counts the occurrences of visual words in the image. This histogram is known as the Bag of Words representation.
4. Train a Classifier: Train a machine learning classifier (e.g., SVM or Random Forest) on the Bag of Words representations of the training images, labeling them as positive (contains the object) or negative (does not contain the object).
5. Object Detection: Apply the trained classifier to new, unseen images to detect the object of interest.

Detecting Cars:

In our experiment, we will focus on detecting cars in a scene using the BOW model. We'll use a dataset of images containing cars and background scenes for training.

Example:



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Let's take a look at a simplified example of how this process might work in Python:

Code:-

```
import cv2
import numpy as np

# Load training images containing cars
car_images = [cv2.imread(car) for car in os.listdir("car_dataset")]

# Extract features (e.g., SIFT) from car images
car_features = [extract_features(image) for image in car_images]

# Cluster features to create a vocabulary
vocabulary = create_vocabulary(car_features)

# Create Bag of Words representations for training images
training_data = create_bow_representation(car_images, vocabulary)

# Train a classifier (e.g., SVM)
classifier = train_classifier(training_data, labels)

# Load a test image
test_image = cv2.imread('test_scene.jpg')

# Extract features from the test image
test_features = extract_features(test_image)

# Create a Bag of Words representation for the test image
test_representation = create_bow_representation([test_image], vocabulary)

# Use the trained classifier to detect cars
result = classifier.predict(test_representation)

# Display the result
if result == 'car':
    print('Car detected!')
else:
    print('No car detected!')
```



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Output:-

Input Image



Output:

Car detected!

Conclusion:-

In this experiment, we explored the process of creating and training an object detector using the Bag of Words model in computer vision. Object detection is a fundamental task with numerous applications in various domains. The BOW model, which is an effective representation technique, allows us to detect objects in images by leveraging local features and machine learning classifiers. The success of the detector depends on the quality and diversity of the training data, as well as the choice of features and classifier. Further optimization and fine-tuning can lead to more accurate and robust object detection systems.