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Practical no 09

Aim: To Creating and Training an Object Detector

Objective: Bag of Words BOW in computer version Detecting cars in a scene.

Theory :

Creating and Training an object detector:-

Using built-in features makes it easy to come up with a quick prototype for an application. and we're all very grateful to the OpenCV developers for making great features, such as face detection or people detection readily available (truly, we are). However, whether you are a hobbyist or a computer vision professional, it's unlikely that you will only deal with people and faces:

Bag-of –words:-

Bag-of-words (BOW) is a concept that was not mitially intended for computer vision, rather, we use an evolved version of this concept in the context of computer vision. So, let's first talk about its basic version, which-as you may have guessed-originally belongs to the field of language analysis and information retrieval. BOW is the technique by which we assign a count weight to each word in a series of documents; we then represent these documents with vectors that represent these set of counts. Let's look at an example:

Document 1: like OpenCV and I like Python
Document 2: like C++ and Python
Document 3: don't like artichokes

BOW in Computer Vision :-

We are by now familiar with the concept of image features. We've used feature extractors, such as SIFT, and SURF, to extract features from images so that we could match these features in another image. We've also familiarized ourselves with the concept of codebook, and we know about SVM, a model that can be fed a set of features and utilizes complex algorithms to classify train data, and can predict the classification of new data.

So, the implementation of a BOW approach will involve the following steps:

1. Take a sample dataset.

2. For each image in the dataset, extract descriptors (with SIFT, SURF, and so on).

3. Add each descriptor to the BOW trainer.

4. Cluster the descriptors to k clusters (okay, this sounds obscure, but bear with me) whose centers (centroids) are our visual words.

Detecting ears

There is no virtual limit to the type of objects you can detect in your images and videos. However, to obtain an acceptable level of accuracy, you need a sufficiently large dataset. containing train images that are identical in size. This would be a time-consuming operation if we were to do it all by ourselves

Example – car detection in a scene

We are now ready to apply all the concepts we leamed so far to a real-life example, and create a car detector application that scans an image and draws rectangles around cars.

Let's summarize the process before diving into the code:

1. Obtain a train dataset.

2. Create a BOW trainer and create a visual vocabulary.

3. Train an SVM with the vocabulary.

4. Attempt detection using sliding windows on an image pyramid of a test image.

5. Apply non-maximum suppression to overlapping boxes.

6. Output the result.

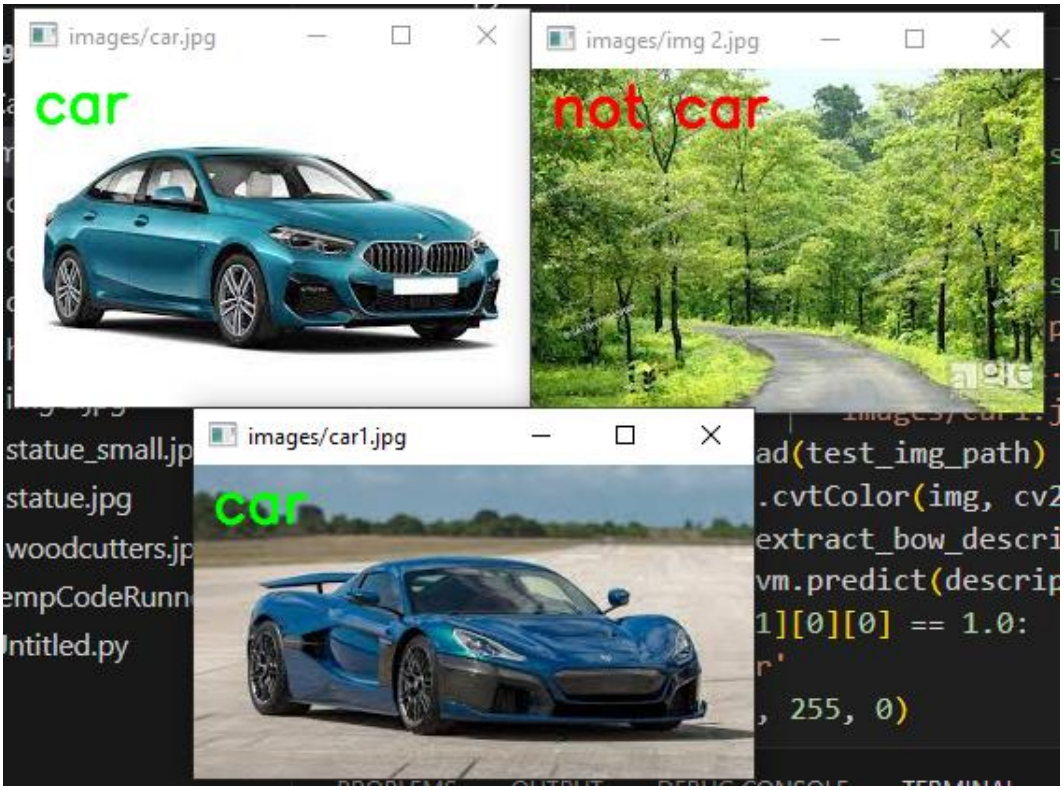
Code :-

```
import cv2
import numpy as np
import os

# Check if the 'CarData' directory exists
if not os.path.isdir('CarData'):
    exit(1)

# Define constants for the number of training samples and BoW clusters
BOW_NUM_TRAINING_SAMPLES_PER_CLASS = 10
SVM_NUM_TRAINING_SAMPLES_PER_CLASS = 110
BOW_NUM_CLUSTERS = 40

# Create a SIFT detector
sift = cv2.SIFT_create()

# Define FLANN parameters for BoW matching
FLANN_INDEX_KDTREE = 1
index_params = dict(algorithm=FLANN_INDEX_KDTREE, trees=5)
search_params = dict(checks=50)
flann = cv2.FlannBasedMatcher(index_params, search_params)

# Create a BoW K-Means trainer and BoW image descriptor extractor
bow_kmeans_trainer = cv2.BOWKMeansTrainer(BOW_NUM_CLUSTERS)
bow_extractor = cv2.BOWImgDescriptorExtractor(sift, flann)

# Function to get positive and negative image paths
def get_pos_and_neg_paths(i):
    pos_path = 'CarData/TrainImages/pos-%d.pgm' % (i+1)
    neg_path = 'CarData/TrainImages/neg-%d.pgm' % (i+1)
    return pos_path, neg_path

# Function to add SIFT descriptors to the BoW trainer
def add_sample(path):
    img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)
    keypoints, descriptors = sift.detectAndCompute(img, None)
    if descriptors is not None:
```

```
        bow_kmeans_trainer.add(descriptors)

# Loop to add samples to the BoW trainer
for i in range(BOW_NUM_TRAINING_SAMPLES_PER_CLASS):
    pos_path, neg_path = get_pos_and_neg_paths(i)
    add_sample(pos_path)
    add_sample(neg_path)

# Cluster the SIFT descriptors to form the vocabulary
voc = bow_kmeans_trainer.cluster()
bow_extractor.setVocabulary(voc)

# Function to extract BoW descriptors
def extract_bow_descriptors(img):
    features = sift.detect(img)
    return bow_extractor.compute(img, features)

# Lists to store training data and labels
training_data = []
training_labels = []

# Loop to extract BoW descriptors for training data
for i in range(SVM_NUM_TRAINING_SAMPLES_PER_CLASS):
    pos_path, neg_path = get_pos_and_neg_paths(i)
    pos_img = cv2.imread(pos_path, cv2.IMREAD_GRAYSCALE)
    pos_descriptors = extract_bow_descriptors(pos_img)
    if pos_descriptors is not None:
        training_data.extend(pos_descriptors)
        training_labels.append(1)  # Positive class
    neg_img = cv2.imread(neg_path, cv2.IMREAD_GRAYSCALE)
    neg_descriptors = extract_bow_descriptors(neg_img)
    if neg_descriptors is not None:
        training_data.extend(neg_descriptors)
        training_labels.append(-1)  # Negative class

# Create an SVM classifier
svm = cv2.ml.SVM_create()

# Train the SVM using the training data
svm.train(np.array(training_data), cv2.ml.ROW_SAMPLE,
np.array(training_labels))
```

```
# Loop to test the classifier on test images
for test_img_path in ['CarData/TestImages/test-0.pgm',
                      'CarData/TestImages/test-1.pgm',
                      'images/car.jpg',
                      'images/haying.jpg',
                      'images/statue.jpg',
                      'images/woodcutters.jpg',
                      'images/download.jpeg']:
    img = cv2.imread(test_img_path)
    gray_img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    descriptors = extract_bow_descriptors(gray_img)
    prediction = svm.predict(descriptors)
    if prediction[1][0][0] == 1.0:
        text = 'car'
        color = (0, 255, 0)
    else:
        text = 'not car'
        color = (0, 0, 255)
    cv2.putText(img, text, (10, 30), cv2.FONT_HERSHEY_SIMPLEX, 1, color,
2, cv2.LINE_AA)
    cv2.imshow(test_img_path, img)

# Display the test results
cv2.waitKey(0)
```

OUTPUT :-



Conclusion :-

In the domain of computer vision, the Bag-of-Words model (BoW model), also known as the Bag-of-Visual-Words model, is a powerful approach applied to tasks such as image classification and retrieval. It treats visual features within images as if they were words in a text document. This BoW model operates through a series of key stages, starting with feature extraction, followed by codebook generation, and concluding with feature vector generation. Leveraging the BoW model, a program for detecting cars within a scene has been developed, effectively determining whether a given scene contains a car or not.