B657 Computer Vision

PARKING LOT CLASSIFICATION

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1 Introduction and Background

- Finding a vacant space in parking lots of large metropolitan areas may frequently become exhausting. Apart from being stressful, this challenging task usually consumes considerable time and money. In addition, it contributes to the pollution of the environment with CO2 emissions.
- Though there are number of solutions based on different technologies, we advocate the use of image/video processing.
- We are using a subset of PKLot Dataset[1] that contains 100,000 images of parking spaces segmented out from 12,000 images of parking lots under different weather conditions.
- Using random sampling we divided the dataset for training and testing purposes. 70 percent was used for training and 30 percent was used for testing and accuracy calculations.

2 Analysis and Design

- First, the multi-orientation representations are derived by convolving the parking space image with Gabor filters.
- Second LBP operator is applied on the transformed images of Gabor filter thus giving us the final features. In this way, we encode the neighboring information and the texture information not only in image space but also among different orientations.



Figure 1: Project Flow

Gabor Filters

A family of Gabor kernel is the product of a Gaussian envelope and a plane wave[2]:

$$\psi_k(z) = \frac{k^2}{\sigma^2} exp\left(-\frac{k^2}{2\sigma^2}z^2\right) \left(exp(ikz) - exp\left(-\frac{\sigma^2}{2}\right)\right)$$

Gabor wavelets capture the local structure corresponding to specific spatial frequency, spatial locality, and selective orientation which are demonstrated to be discriminative and robust to illumination and expression changes. Given an image I(x,y), its Gabor transformation at a particular position can be computed by a convolution with the Gabor kernels given by[2]:

$$G_k(x,y) = I(x,y) * \psi(x,y)$$



Figure 2: Gabor filters with 4 orientations

Local Binary Pattern

LBP is a powerful method of texture description based on statistical analysis and shows its practical use in texture description. The operator labels pixels of an image by thresholding the 3x3 neighborhood of each pixel with the center pixel and considering the result as a binary number. The LBP result can be expressed as follows[2]:

$$LBP_{P,R} = \sum_{n=0}^{7} \delta(g_n - g_c) 2^n$$

Where gc is a center pixel value positioned at (xc,yc), gn is one of the eight surrounding center pixel values with the radius R, P is the whole neighborhood number, and a sign function is defined such that[2]:

$$\delta(x) = 1 \quad if x > 0$$

= 0 (1)



Figure 3: LBP operator algorithm

3 Implementation

We used python as our language and imported OpenCV library. We trained our data using classifiers like SVM and logistic regression from the scikit-learn package. gabor_convolution.py parses the directory and takes each segmented image. 5x5 Gabor filters are generated by build_filters()(refer [3]) with following parameters:

- ksize = 5
- sigma = 4.0
- theta = 4 orientations 0, 45, 90, 135 degrees
- lambd = 10.0
- gamma = 0.5
- psi = 0
- ktype = CV_32F

These filters are then convolved on the segmented images and lbp_image() calculates the LBP of the image. The final image is our feature vector. The data set generated after this pre-processing was divided into 2 parts - Train (80%) and test (20%). The Train data was trained using classifier like 'Logistic Regression' and 'SVM', with different parameter settings. Each model was evaluated on test dataset.

4 Testing

After we had trained the model, for testing we took help of the segmented section of the PKLot dataset where each parking space was separated and was annotated by date and time and the parking lot type. The space to be tested was passed through the gabor filter and features were generated of this image using LBP. This input when fed to the model would give a binary output as 0 or 1, 0 signifying that the space being vacant and 1 signifying that the parking space is occupied.

5 Results

Metric	Logistic Regression					SVM				
Hyper parameter	20	10	0.1	0.01	0.001	20	10	0.1	0.01	0.001
Recall	0.94	0.94	0.94	0.94	0.94	0.98	0.98	0.97	0.93	0.86
Precision	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.98
AUC-ROC	0.95	0.95	0.95	0.95	0.95	0.98	0.98	0.97	0.96	0.92
Accuracy	94.76	94.76	94.76	94.76	94.76	98.08	98.08	97.79	94.92	90.16



(a) Pecision Histogram

20 10 0.1 0.01 0.001

SVM

AUC-ROC

10 0.1 0.01 0.001

AUC-ROC 0.95 0.95 0.95 0.95 0.95 0.98 0.98 0.97 0.96 0.92

(c) AUC-ROC

Logistic Regression





Accuracy

(b) Recall Histogram



Accuracy 94.76 94.76 94.76 94.76 94.76 94.76 98.08 98.08 97.79 94.92 90.16

Logistic Regression

SVM



6 Analysis

0.99

0.98

0.97 0.96

0.95

0.94

0.93

0.91

0.9 0.89

20

As we wanted focus on to get accurate prediction for 'presence of car' in parking spot, we decided to use evaluation measure like 'Recall' and 'AUC-ROC'. With Logistic regression, 'Recall' and 'Precision' was almost same for all hyper-parameters. In case of SVM, 'Recall' increases with increase in value of hyper-parameter 'C', which indicate that SVM was overfitting initially Parking Lot Classification

with smll values of 'C', but as with introduction of bias, it generalized more smoothly. We used Gaussian Kernel for SVM and it perform better that Linear Kernel.

7 Challenges, Conclusion and Future Work

The main problem that we were trying to address was whether we can determine a particular parking space was occupied or not. While creating the model, we had to take care of the below concerns:

- The model should be invariant to the changes in lightning conditions caused by sunny, overcast and rainy days. Selection of features from image.
- The current model does not detect parking spaces from parking lots. The position of the parking spaces are obtained by parsing the corresponding xml manually with respect to camera position.

We were able to achieve this with 98.08 percent accuracy. Also during discussion with fellow researchers in Computer Vision, we realized that our model will not be very useful for extreme weather conditions like completely snow-covered parking lots.

We conclude the following:

- Effectively used image/video processing instead of sensor or parking meters to identify whether we have empty parking spaces in a parking lot.
- Designed innovative features for classification.
- Accurately identified the availability of an empty parking space in a parking lot.

Future Work

- Comparison of accuracy generated by CNN and our method.
- Identifying the parking spaces in the parking lot with respect to different camera angles.
- Exploring other methods that can further improve the accuracy.
- Using video data from parking lot for classification instead of Images.
- Design an algorithm that can identify parking space based on parking space boundary.

8 References

[1] de Almeida, Paulo RL, et al."PKLotâĂŞA robust dataset for parking lot classification." *Expert Systems with Applications* 42.11 (2015): 4937-4949.

[2] Zhou, Shu-Ren, Jian-Ping Yin, and Jian-Ming Zhang. "Local binary pattern (LBP) and local phase quantization (LBQ) based on Gabor filter for face representation." *Neurocomputing* 116 (2013): 260-264.

[3] < https://cvtuts.wordpress.com/2014/04/27/gabor-filters-a-practical-overview/>