Parking Spot Detection from Aerial Images

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***Abstract*—Finding an available parking spot in big and crowded city centers has been an important problem for people who use their own cars for transportation. Hence, parking spot detection has been an interesting problem that has drawn considerable attention. Although parking spot detection using ground based camera imagery has been studied extensively, doing the same using aerial images is a relatively unexplored problem. In this work we present a machine learning based approach for the latter.**

I. Introduction

AUTOMATIC parking spot detection using digital imagery became an important application area for the last decade as digital visual information become easily accessible. Surveying the literature one sees that researchers have analyzed the general problem in two particular contexts. In the first one digital imagery obtained from ground based cameras are used to classify parking spots in a parking lot and/or on a street. This particular setting has been studied pretty extensively. In particular, [1] and [2] are good examples of such work. In the second context, digital aerial imagery is used to classify parking spots in a parking lot. Again, [3] and [4] can be given as examples. In this work we generalize the second context and present a method to classify both parking lot and street parking spaces using digital aerial imagery. Outline of the developed method is given below.

Input: Training and test sets of aerial images with labelled parking spots.

Parameters: Minimum segment area

1: Generate an Luv color space representation of the image.
2: Segmentate the image using the Luv color space representation.
3: Extract features.
4: Use a binary SVM with linear kernel to classify the parking spots.

Output: Prediction results on the test set.

Image segmentation was done using the publicly available mean shift image segmentation implementation EDISON [5]. For the last step we used the popular LIBLINEAR [6] package for the SVM. These steps will be explained in further detail in the following sections.

II. Data Acquisition

We used the well known software Google Earth [7] to obtain the aerial imagery used in this work. The location was randomly chosen to be Cambridge, UK. Eye altitude and resolution are 433 ft and 1664×1091 respectively. Seven images have been used to provide data for both training and test sets. Parking spots on these images were marked manually. Each parking spot is represented by a smaller 60×60 subimage. In figure 1 we give an example image with the marked parking spots.

Fig. 1. Example image with marked parking spots

Fig. 2. Example segmented image. Minimum segment area is 200 pixel^2.

III. Image Segmentation

Image segmentation is an important part of the algorithm since many features are extracted from the data obtained through image segmentation. Although there are many algorithms for image segmentation (i.e. k-means, statistical region merging, mean shift etc.), we found mean shift based algorithms suit best for the purpose of this work. Although image segmentation algorithms have many tuning parameters, default values of all parameters except the minimum segment area work fine in our algorithm. Minimum segment area thus becomes the only tuning parameter of our algorithm that stems from image segmentation. In figure 2 we give an an example segmented image.

TABLE I
FEATURE LIST

Feature #	Explanation
Feature 1 :	$\min_i \|\|x_{ij} - s_j\|\|_2$ where s_j is the center of the parking spot in question and x_{ij} is the mean coordinates of i'th segment touching the parking spot in question.
Feature 2 :	Area of the segment found above.
Feature 3 :	|Average grayscale color value of the parking spot − Average grayscale color value of the center region of the parking spot|
Feature 4 :	Standard deviation of the grayscale color value of the center region of the parking spot.
Feature 5 :	Luv color values of the segment with the maximum area touching the parking spot in question.
Feature 6 :	|| The above color vector - Luv color of the segment found in feature $1\|\|_2$
Feature 7 :	Luv color of the segment including the center of the parking spot in question.
Feature 8 :	Area of the maximum area segment touching the parking spot in question.

IV. FEATURE EXTRACTION

This is arguably the most crucial part of the algorithm. In the literature, feature extraction is unfortunately overlooked in the context of parking spot detection. Raw pixel information and shallow statistics thereof (e.g. histograms) are almost exclusively used. This, however, results in poor performance in many cases. We used a heterogenous set of features incorporating a wide range of information; including geometrical, optical and statistical information. The full list of the features are given in table I. In this table, "center region" of a parking spot means the $L/2 \times L/2$ sub image having the same center with the parking spot image. Here $L = 60$ is the side length of a parking spot image.

Feature selection

Our intution led us to think that each feature captures different information and thus is necessary. To validate the necessity of each individual feature, an exhaustive search for the best feature combination was performed. Best 80% hold-out cross validation accuracy was achieved with the full set of features.

V. SUPPORT VECTOR MACHINE

Although we tried many different kernels and solvers, the best kernel/solver combination for this problem was found to be linear kernel and l_2 regularized logistic regression (primal). The cost parameter of the SVM and the error tolerance of the solver is found to have little effect on the performance of the algorithm. Particular values that are found to work well are $C = 1$ and $\epsilon = 10^{-6}$. Finally, we used the LIBLINEAR software as our implementation of choice.

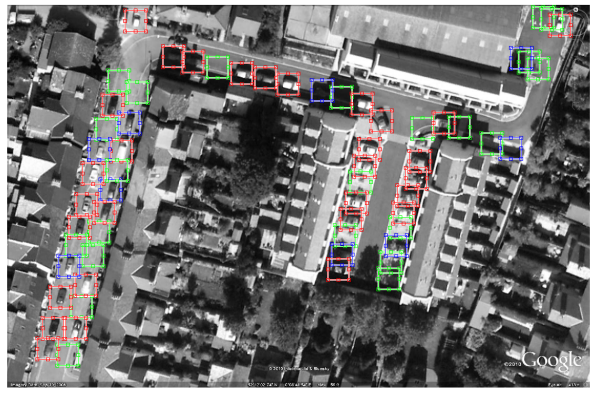

Fig. 3. Typical result with 80% hold out cross validation. Spots correctly marked as "available" are marked in green whereas spots correctly marked as "occupied" are marked with red. Spots marked in blue are misclassified.

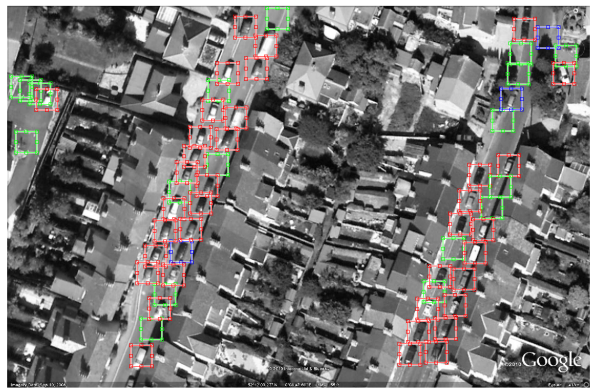

Fig. 4. Another typical result with 80% hold out cross validation.

TABLE II
CONFUSION MATRIX FOR THE TRAINING SET

Case	Real Available	Real Occupied
Predicted Available	125	10
Predicted Occupied	10	205

VI. RESULTS

We used 80% hold out cross validation to measure the performance parameters of the algorithm. Results for a typical run are given in figure 4 and performance metrics are summarized in tables II, III and IV.

Sensitivity analysis on "Minimum Segment Area" parameter

Being the only non machine learning parameter of the algorithm, minimum segment area warrants a sensitivity analysis. As seen in figure 5, the algorithm is robust with respect to changes in the parameter. The plot also shows that the chosen value of 200 pixel^2 is indeed a good choice for a reasonable balance between precision, recall and specificity.

VII. DISCUSSION AND FUTURE WORK

First of all, we actually wanted to plot the precision-recall curve of our detector as well. However, LIBLINEAR software

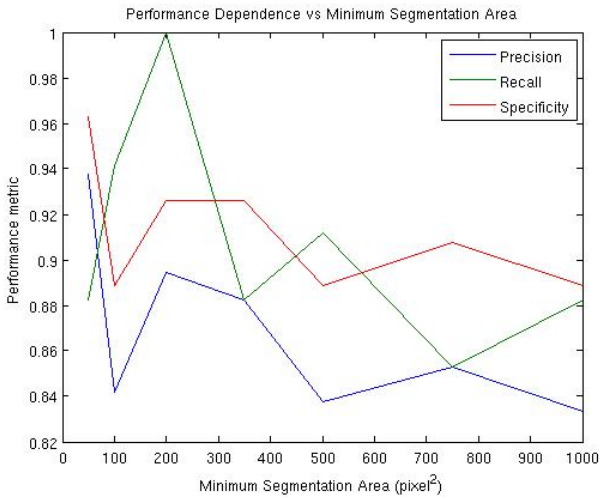

Fig. 5. Sensitivity analysis on the parameter "Minimum Segment Area"

TABLE III
CONFUSION MATRIX FOR THE TEST SET

Case	Real Available	Real Occupied
Predicted Available	30	2
Predicted Occupied	4	52

TABLE IV
PERFORMANCE METRICS FOR THE TEST SET

Metric	Percentage (%)
Training Accuracy	94.29
Test Accuracy	93.18
Test Recall	88.24
Test Precision	93.75
Test Specificity	96.30

does not give us the freedom to apply a bias for certain solvers (probably due to a bug). Unfortunately, the solver that works well in our problem happens to be one of these "problematic" solvers.

Tables showing the performance metrics indicate that the algorithm works pretty well compared to similar work in the literature. Thus, future work should probably be concentrated on expanding the functionality of the detector instead of trying to squeeze a little more performance out of it. One of the main possible future additions could be using a three class SVM to automatically classify non-parking regions in an image. This would eliminate the need for a human operator to mark parking spots in test data. This would make the algorithm much more useful in real life applications. One way to achieve this would be extracting road information from the images and using the distance to road edges as a new feature.

VIII. CONCLUSION

In this work we presented a new algorithm to generalize automatic parking spot detection to street parking in addition to parking lots. The main stages of the algorithm are image segmentation, feature extraction and classification using an SVM with linear kernel; feature extraction being the most critical step. Results show that the algorithm works pretty well compared to similar work in the literature. While working on the project, we also realized an important possible future extension that could lead to a new and practical technology which could make lives of drivers much easier.

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