

CAR CONTEXT HEAT MAP FOR FAST EXPLORATION

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ABSTRACT

- Exploration: find all cars in a terrain as fast as possible
- Problem: what to do when the object is not in sight?
- Trained car context classifier with 272 aerial images with hand-labeled cars
- Obtained 65.4% and 79.5% accuracy with Neural Net classifier using low (2^{nd} layer) and high level (6^{th} layer) features extracted from AlexNet

MOTIVATION



Figure 1: Exploration of objects such as cars or animals in an open environment, or search-and-rescue missions

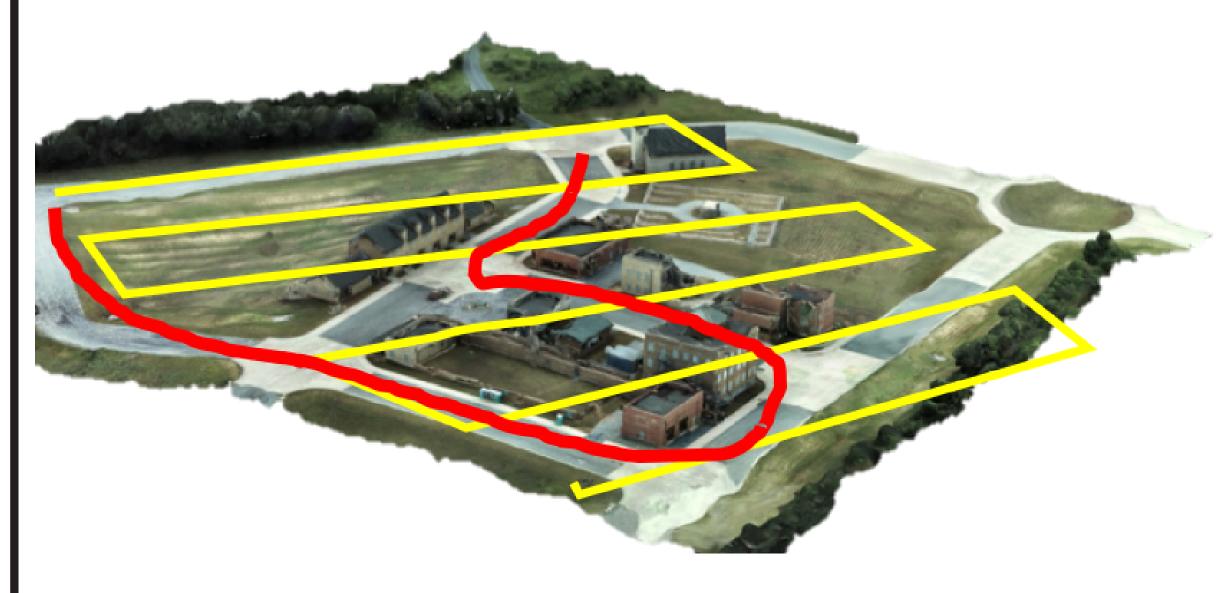


Figure 2: Focused exploration leads to more relevant information

METHODS

We extracted features from regions close and far away from cars in 272 manually labeled examples.

We trained a binary classifier to distinguish between our two classes: positive for being close to a car and negative for being distant form a car. We implemented two approaches:

Step	Description
Region selection	Select patches in blobs close and far away to the labeled car
Feature extraction	(1) Extract features from the 2^{nd} layer of AlexNet — 100K samples with 96 features each
	(2) Extract features from the 6^{th} layer of AlexNet — 3K samples with 4096 features each
Training	Train a binary neural network classifier to output probability of patch being close to a car
Quantitative test	Evaluate performance of classifier on test set
Qualitative test	Break down an entire image in patches and evaluate qualitatively its heat map

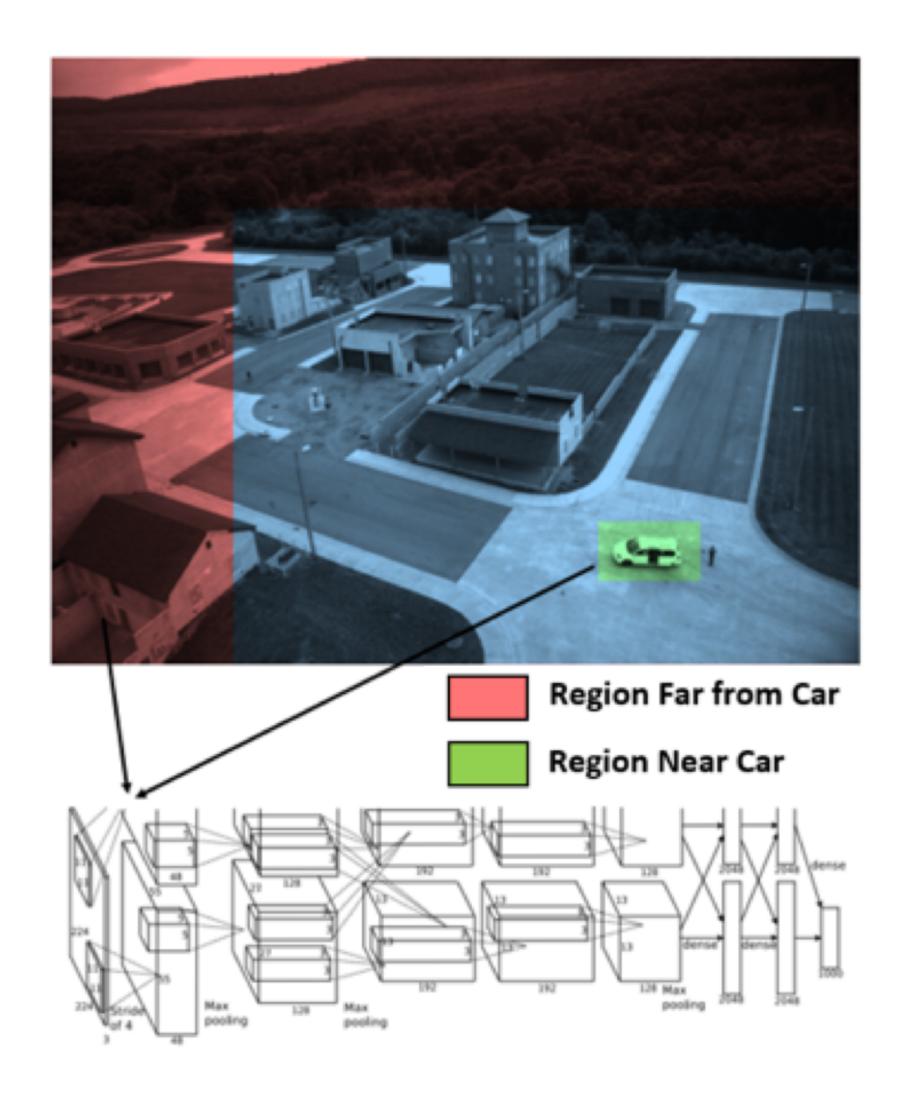


Figure 3: Feature extraction from candidate regions of an image

HEAT MAPS OF CAR CONTEXT

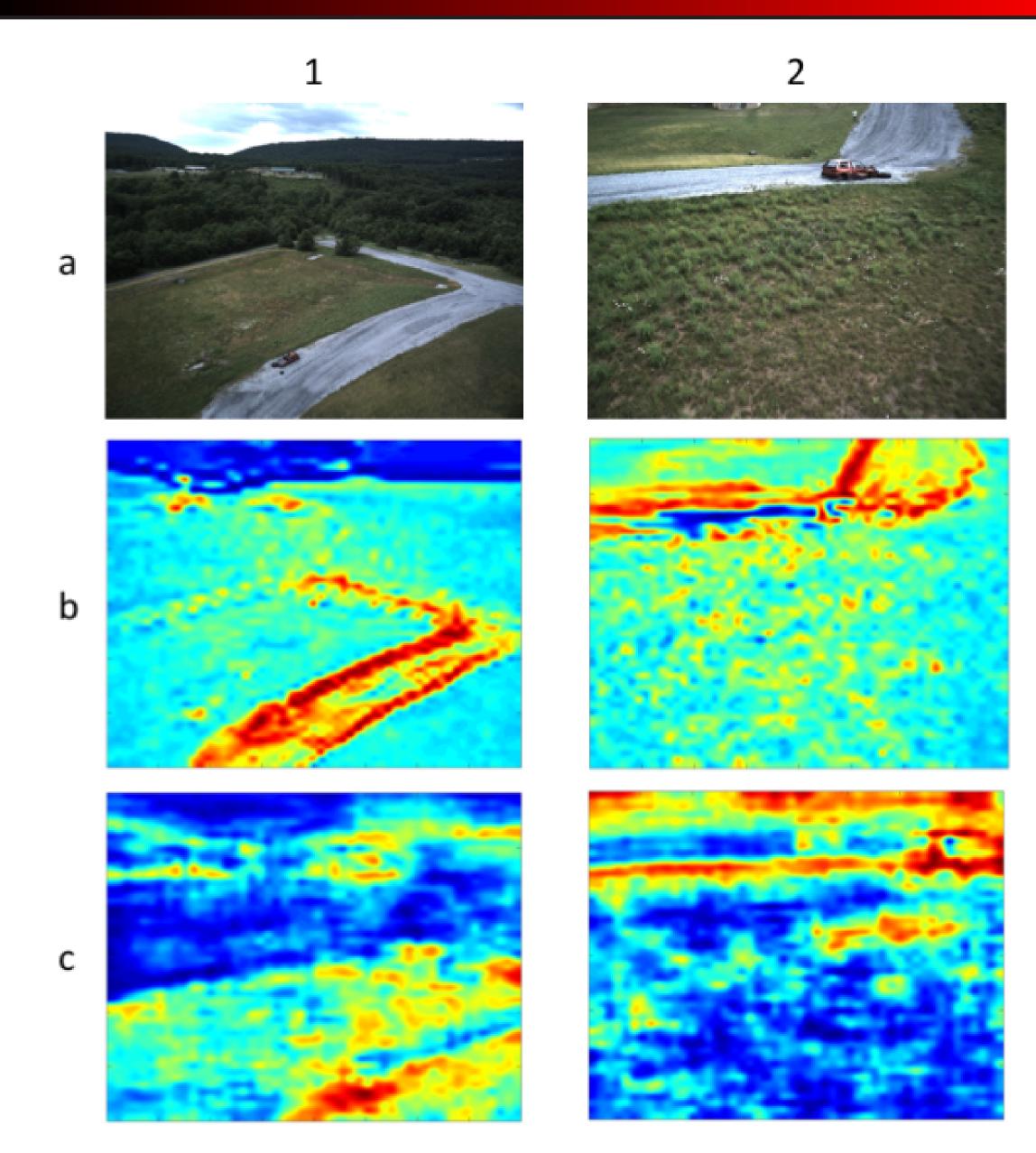


Figure 4: Heat maps generated for two sample images in column 1 and column 2. Row "a" contains the original image, row "b" has the heat map based on low-level features and row "c" has the heatmap based on high-level features from AlexNet

Qualitative evaluation of the images:

- Low-level features from AlexNet identify edges and texture well, as expected
- High-level features generate a more diffuse representation of context
- Images in extremes of scales are not well represented using either method

REFERENCES

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FUTURE WORK

- Employ a combination of high and low level features to identify context (hypercolumns)
- Test different network architectures for both feature extraction and classification
- Use larger dataset and train a convolutional neural network for end-to-end classification

ACKNOWLEDGEMENTS

The authors would like to thank Daniel Maturana from CMU for providing the dataset of aerial images used in this project.