

Classical Computer Vision Still has its Place in Object Detection

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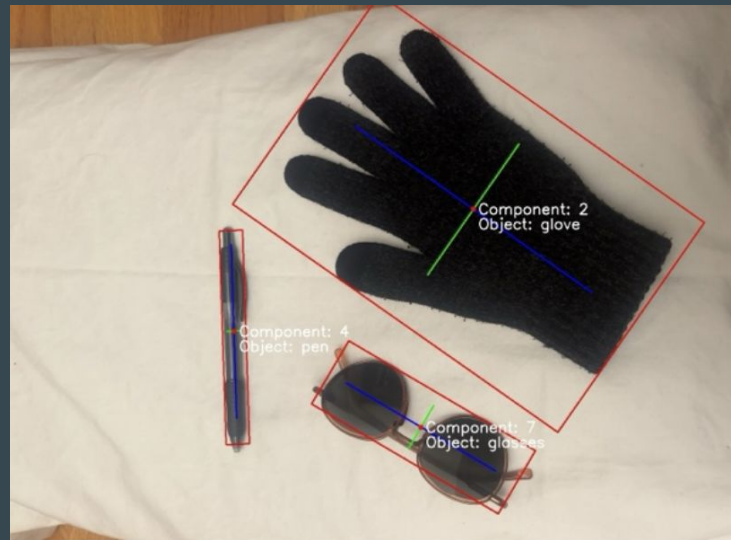
Previous Work

Features:

- Can accurately detect objects at different orientations and scales
- Can learn new objects
- Uses 9 manually calculated features for matching

Limitations:

- Requires good lighting and white background
- Slow (<1 FPS)
- Some errors in matching
- Detects objects where there are none

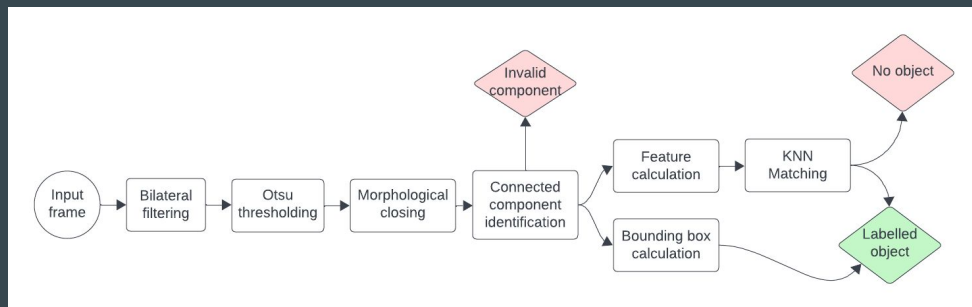


Goals

- Improve classical object detection system
- Implement deep learning based object detection system
- Evaluate and compare the performance of the two systems
- Evaluate the response of the systems to adversarial attacks

Classical Detection Improvements

- Re-implemented in Python for easy integration with deep learning methods
- Thresholding and morphological filtering improved
- Component thresholding introduced
- Improved database handling
 - Normalized database stored in memory
 - Distance threshold (components not identified as objects unless they are nearby in feature space)
 - Easier training (objects can be labelled quickly and easily)
- Higher FPS



Deep Learning

- Implemented 2 transformer models from Hugging Face
- **facebook/DETR-ResNet-50**
 - Larger model: 41.6M parameters
 - Trained on COCO 2017 image dataset with 80 classes
 - Released by Carion et al. from Meta in 2020
- **hustvl/yolos-tiny**
 - Smaller model: 6.5M parameters
 - Trained on ImageNet-1k, then fine-tuned on COCO 2017
 - Released by Fang et al. from

Demo



Adversarial Attacks

- Patches were calculated as in Brown et al.
- Sample images were collected that resemble the testing environment.
- The patch was added with variation in scale, location, and orientation
- Initialize with random noise, the patch is updated by the gradients with respect to the loss function against the target class
- Target classes were remote and car
 - Both classes in ImageNet and COCO
- Can be overlaid both physically and digitally
- The patches were ineffective against the deep learning methods, and only partially effective against the classical method

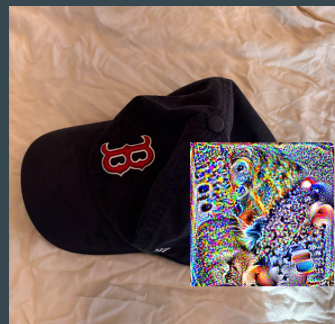
Adversarial Car



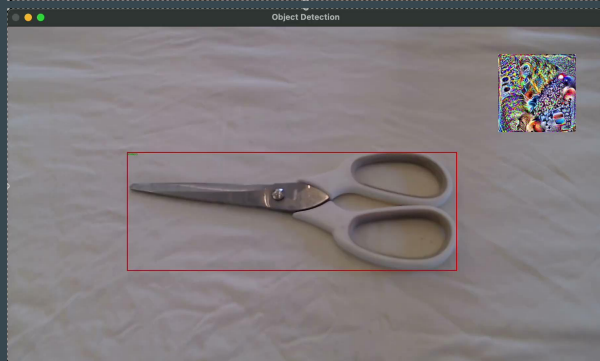
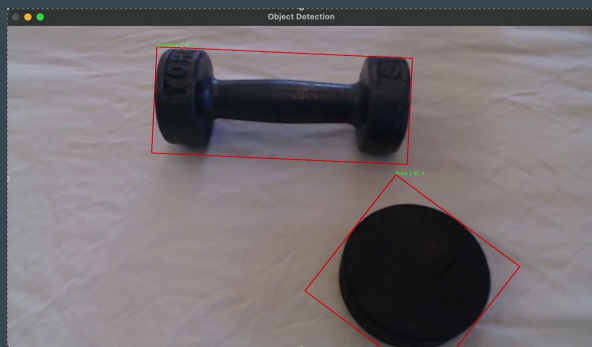
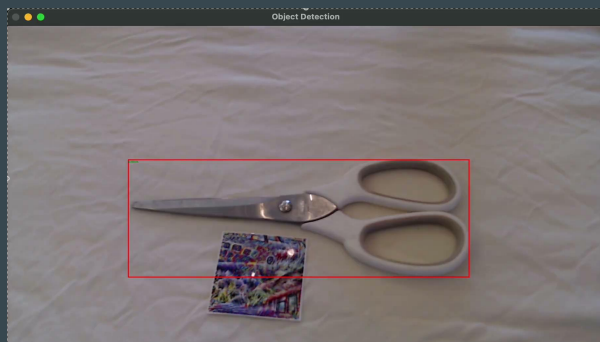
Adversarial Remote



Training example



Adversarial Attacks - Demo



Conclusions

- Classical CV Object Detection
 - Faster frame rates for real time applications
 - Easy to add new classes, training data
 - Worse at generalizing, more situational
 - Struggles with reflective surfaces
- Deep Networks
 - High accuracy, works in many situations
 - Stable in different lighting
 - Slower for real time processing
 - Requires retraining to add new classes
- Adversarial Attacks
 - Ineffective against deep learning methods
 - No more effective than another object