AI for Detection and Classification of Wildlife from UAS Imagery

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USDA

Agenda

1. Motivating Questions

2. UAS image understanding
    1. Data Fusion
    2. Segmentation
    3. Classification

3. Further Questions & Extensions

Papers, Papers & more Papers

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

ELSEVIER

Remote Sensing Environment

Detecting animals in African Savanna with UAVs and the crowds

CrossMark

Nicolas Rey[a], Michele Volpi[b], Stéphane Joost[a,c], Devis Tuia[b,d,*]

sensors

MDPI

Article

A Study on the Detection of Cattle in UAV Images Using Deep Learning

Jayme Garcia Arnal Barbedo [1,*], Luciano Vieira Koenigkan [1], Thiago Teixeira Santos [1] and Patrícia Menezes Santos [2]

Remote Sensing in Ecology and Conservation

Open Access

ZSL LET'S WORK FOR WILDLIFE

INTERDISCIPLINARY PERSPECTIVES

Machine learning to detect marine animals in UAV imagery: effect of morphology, spacing, behaviour and habitat

Antoine M. Dujon[1], Daniel Ierodiaconou[2], Johanna J. Geeson[3], John P. Y. Arnould[3], Blake M. Allan[2], Kostas A. Katselidis[4] & Gail Schofield[1,5]

scholar.google.com/scholar?as_ylo=2021&q=machine+learning+uav+imag...

machine learning uav imagery animal detection classification

Scholar About 10,900 results (**0.06** sec)

Since 2021

Machine learning to **detect** marine **animals** in **UAV imagery**: Effect of morphology, spacing, behaviour and habitat — [PDF] wiley.c

AM Dujon, D Ierodiaconou, JJ Geeson… - Remote **Sensing** in …, 2021 - Wiley Online Library

… computational resources than the **animal detection** step. We … previously applied to **classify** small **images** from a benchmark … of **images** of common **animals** and transportation **machines**. …

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Detection, **identification** and posture recognition of cattle with satellites, aerial photography and **UAVs** using **deep learning** techniques — [PDF] tandfor

CA Mücher, S Los, GJ Franke… - … of Remote **Sensing**, 2022 - Taylor & Francis

… or pixels for the **deep learning classification**) of **imagery** is still time-… AI tools we used for **detecting** cattle and **animal** counting … **detection** of cattle in satellite, aerial and **UAV imagery** are …

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[HTML] **Detecting** sheep in **UAV images** — [HTML] scienc

F Sarwar, A Griffin, SU Rehman, T Pasang - Computers and Electronics in …, 2021 - Elsevier

…) than other **machine learning** algorithms for object **detection**, localization, **classification** and … a fully connected network (FCN) for **livestock detection** in aerial **images** captured by an …

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Rice Seedling **Detection** in **UAV Images** Using Transfer **Learning** and **Machine Learning** — [PDF] mdpi.c

HH Tseng, MD Yang, R Saminathan, YC Hsu… - Remote **Sensing**, 2022 - mdpi.com

… **image** data with many objects to make meaningful **image** analysis [21]. To collect **image** data in agriculture sectors, **UAVs** or **drones** … , weed **classification**, harvesting, **livestock** counting …

Save Cite All 6 versions

Motivating Ques

Environment/ Background

Occlusions

NO Distinguishing features

Small Object Size

Small Annotated Dataset

Motivating Questions

Environment/
Background

Occlusions

NO Distinguishing
features

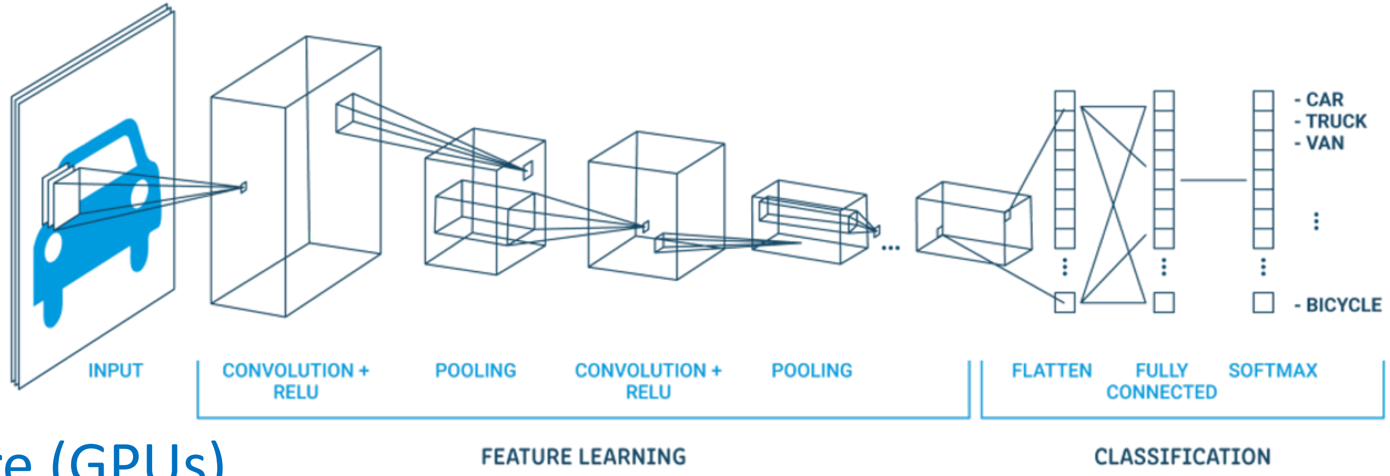
Small Object Size

Small Annotated
Dataset

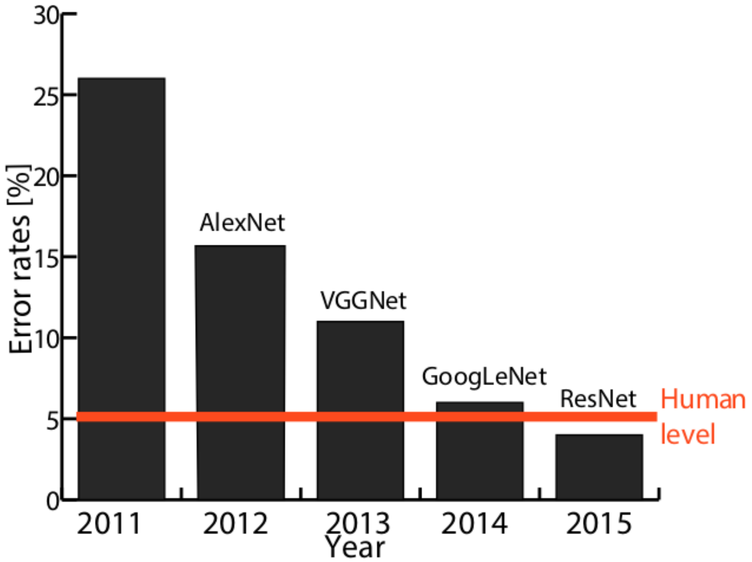
J. Waldchen, P. Mader, *Machine learning for image-based species identification,* Methods in Ecology and Evolution
Redmon et.al.,

UAS Image Understanding ---
Some Experiments

Why is ML successful in classification?



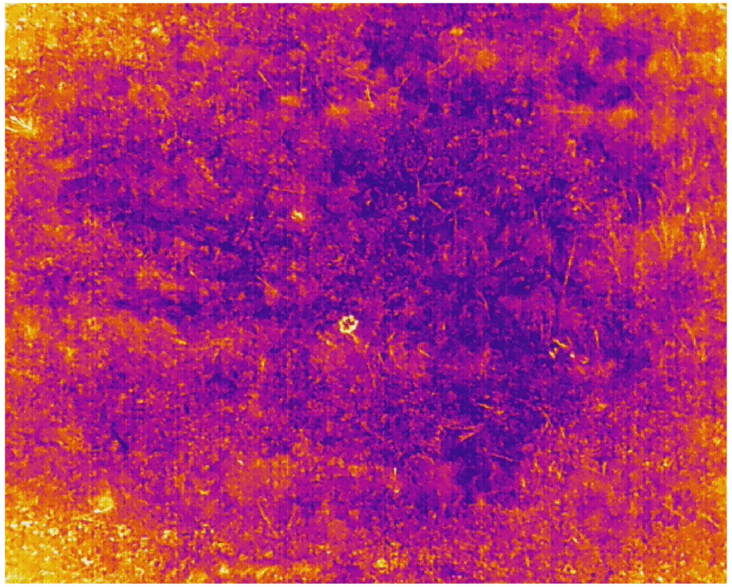
1. faster & powerful computer hardware (GPUs)
2. algorithms tailor-made for these architectures
3. almost unlimited amounts of training data
    1. Images (ImageNet 14,197,122 images ~ ILSVRC '10-'17)
    2. Documents (270 GB of all arXiv research papers,)
    3. Social media posts (Sentiment 140 -160,000 tweets each with 6 data, query, text, polarity, ID, and user)



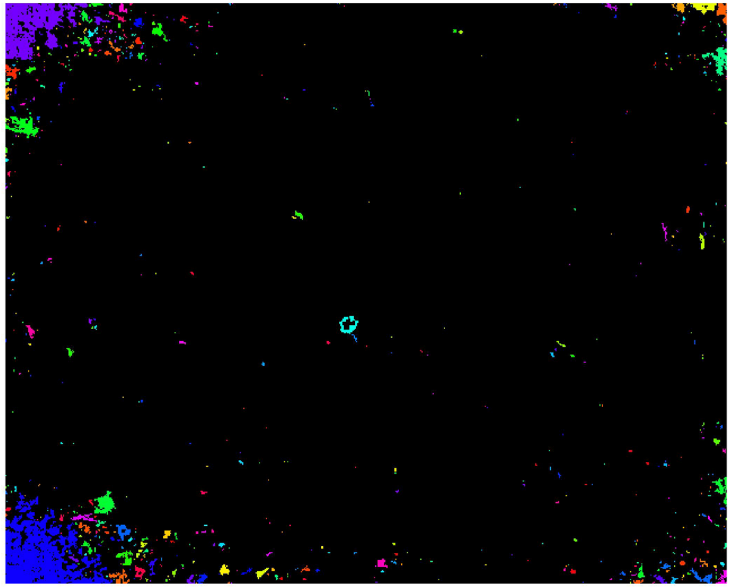
Y. Bengio, A. Courville, P. Vincent, *Representation learning: A review and new perspectives*. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2013
Y. LeCun, Y. Bengio, G. Hinton, *Deep learning*. Nature, 2015
Russakovsky et. al. ResNet, 2015

Quail Covey @Night --- Fusion for Localization

Domain adaptation for RGB object detection by translating the low-level features adopted from source domain (thermal) to target domain (RGB)

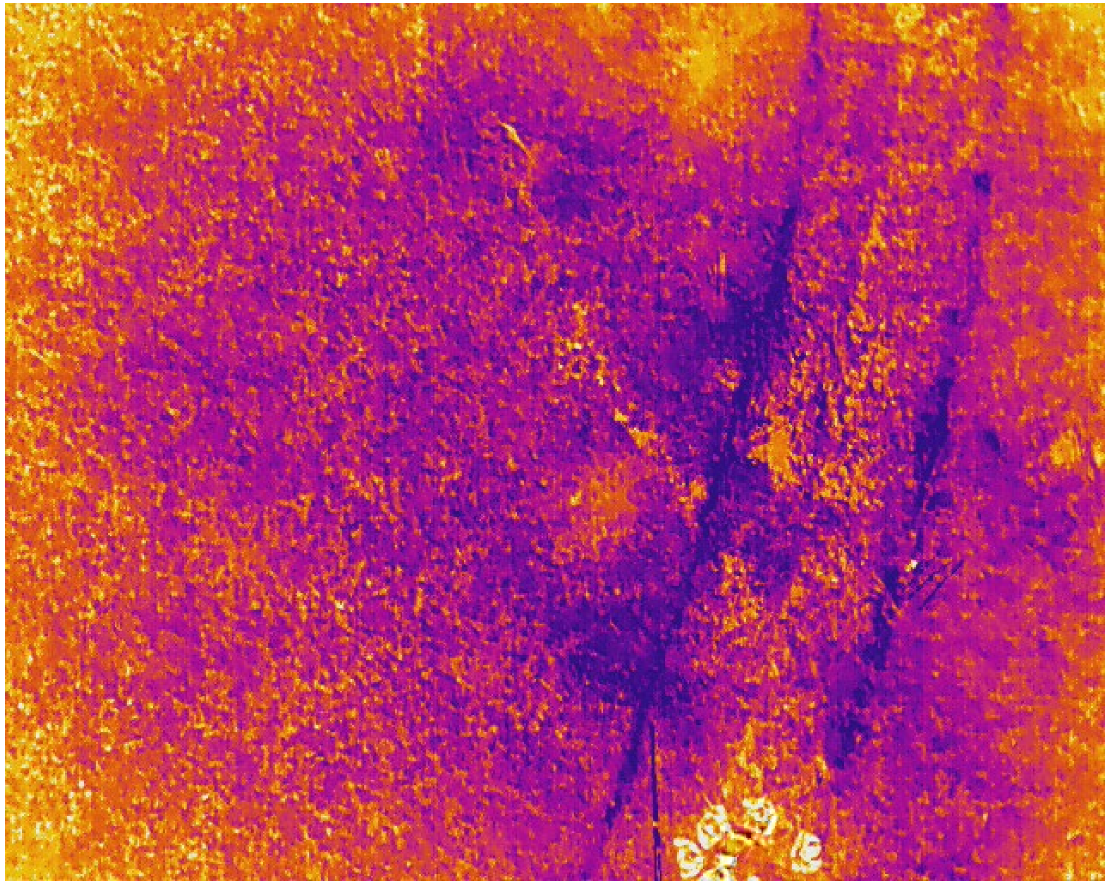


652 - Blobs are detected

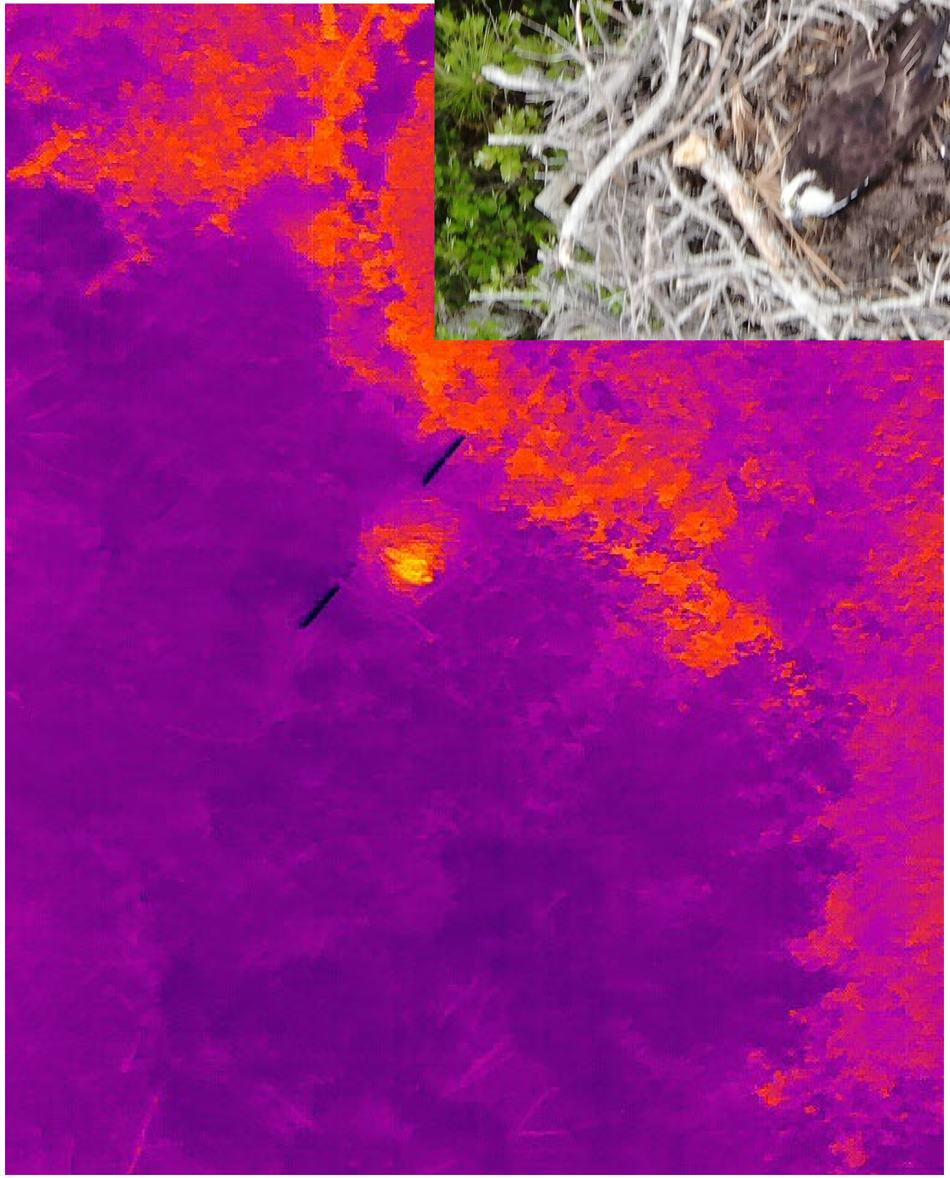


Farzeen Munira et. al, *Exploring Thermal Images for Object Detection in Underexposure Regions for Autonomous Driving,* https://arxiv.org/pdf/2006.00821.pdf

Another night capture attempt of a covey

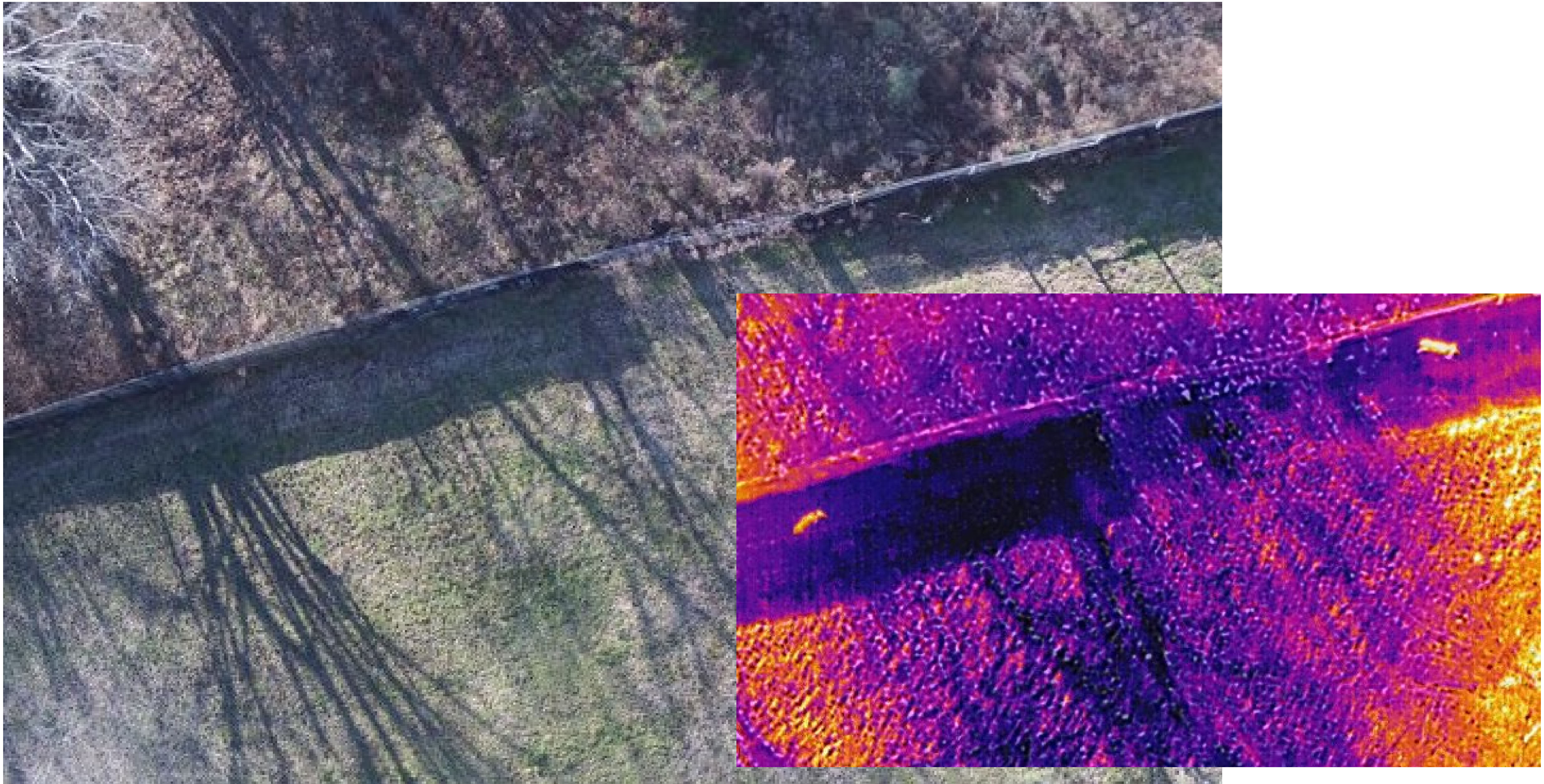


Background clutter removal



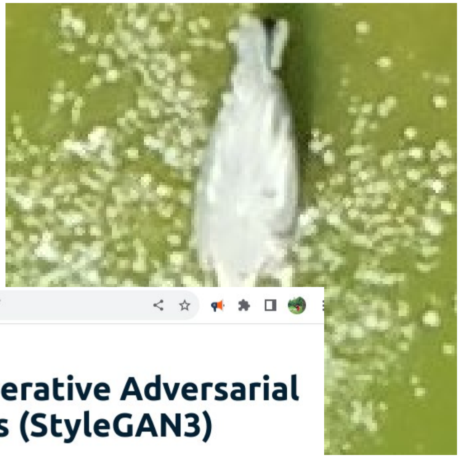
Captured on a Zenmuse H20T @GulfShores in Apr 22

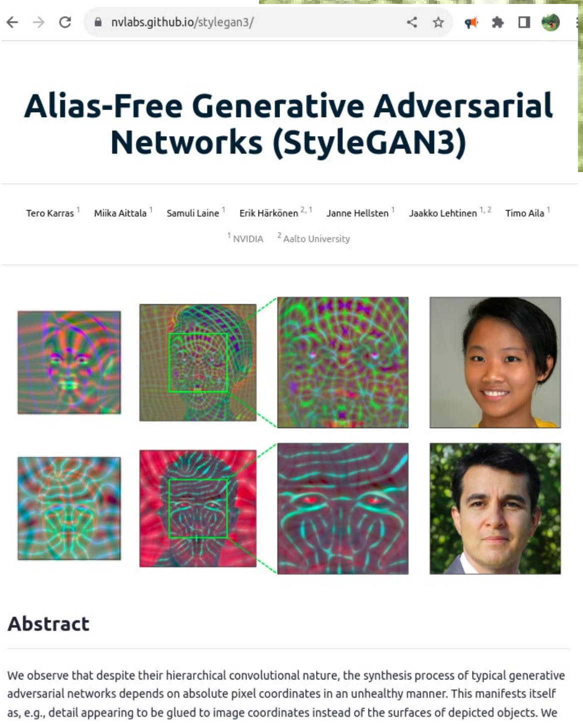
UAS Image Understanding --- Shadow Correction



UAS Image Understanding --- Shadow Contd.

Aerial view -> Background separation & Shadow extraction




nvlabs.github.io/stylegan3/

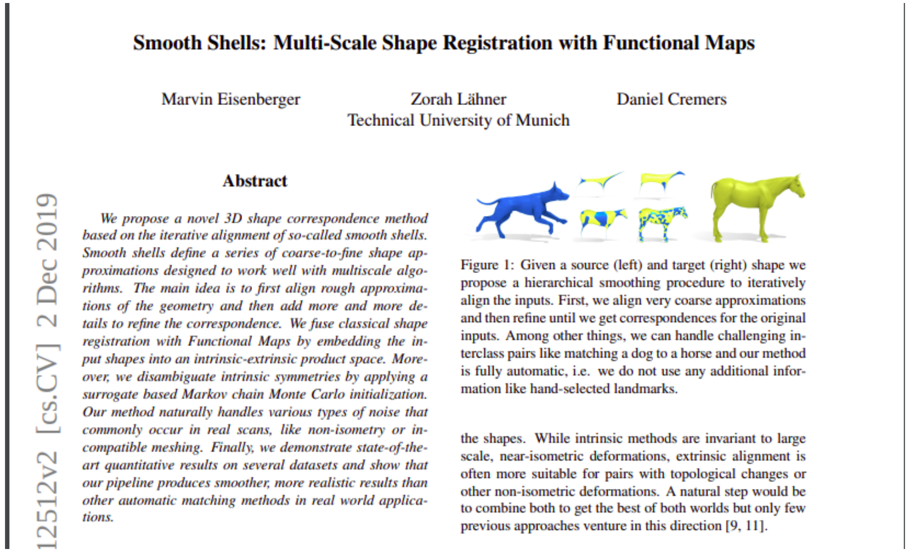
Alias-Free Generative Adversarial Networks (StyleGAN3)

Tero Karras [1] Miika Aittala [1] Samuli Laine [1] Erik Härkönen [2,1] Janne Hellsten [1] Jaakko Lehtinen [1,2] Timo Aila [1]

[1] NVIDIA [2] Aalto University

Abstract

We observe that despite their hierarchical convolutional nature, the synthesis process of typical generative adversarial networks depends on absolute pixel coordinates in an unhealthy manner. This manifests itself as, e.g., detail appearing to be glued to image coordinates instead of the surfaces of depicted objects. We



Smooth Shells: Multi-Scale Shape Registration with Functional Maps

Marvin Eisenberger Zorah Lähner Daniel Cremers

Technical University of Munich

12512v2 [cs.CV] 2 Dec 2019

Abstract

We propose a novel 3D shape correspondence method based on the iterative alignment of so-called smooth shells. Smooth shells define a series of coarse-to-fine shape approximations designed to work well with multiscale algorithms. The main idea is to first align rough approximations of the geometry and then add more and more details to refine the correspondence. We fuse classical shape registration with Functional Maps by embedding the input shapes into an intrinsic-extrinsic product space. Moreover, we disambiguate intrinsic symmetries by applying a surrogate based Markov chain Monte Carlo initialization. Our method naturally handles various types of noise that commonly occur in real scans, like non-isometry or incompatible meshing. Finally, we demonstrate state-of-the-art quantitative results on several datasets and show that our pipeline produces smoother, more realistic results than other automatic matching methods in real world applications.

Figure 1: Given a source (left) and target (right) shape we propose a hierarchical smoothing procedure to iteratively align the inputs. First, we align very coarse approximations and then refine until we get correspondences for the original inputs. Among other things, we can handle challenging interclass pairs like matching a dog to a horse and our method is fully automatic, i.e. we do not use any additional information like hand-selected landmarks.

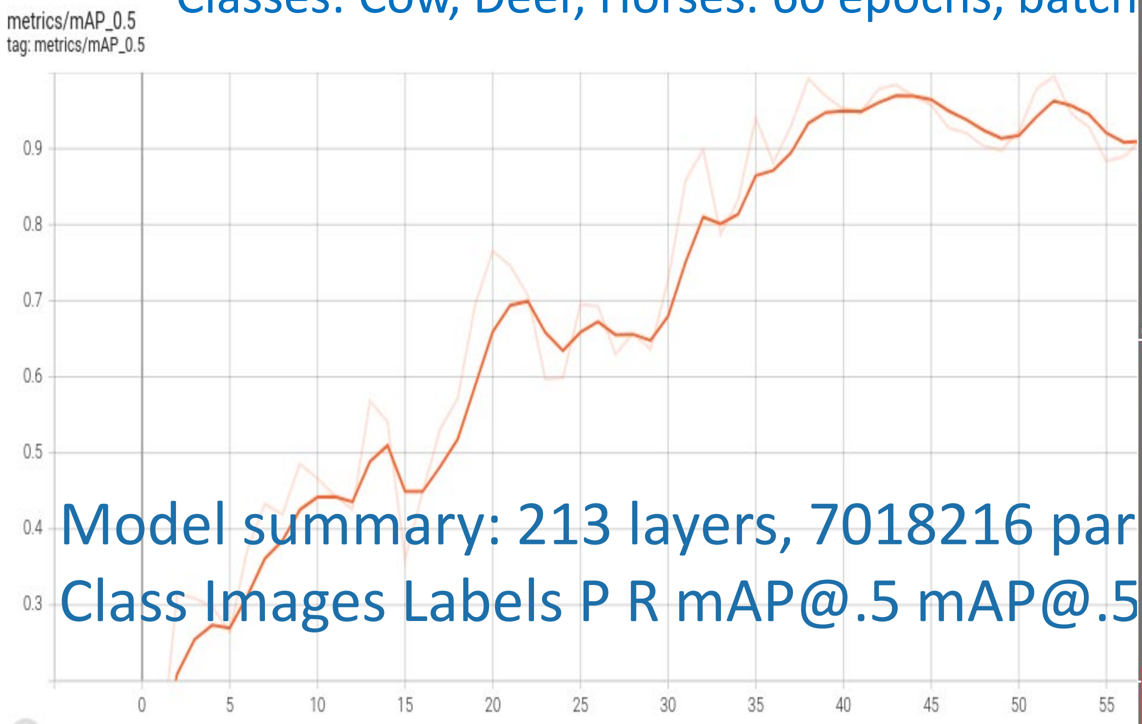
the shapes. While intrinsic methods are invariant to large scale, near-isometric deformations, extrinsic alignment is often more suitable for pairs with topological changes or other non-isometric deformations. A natural step would be to combine both to get the best of both worlds but only few previous approaches venture in this direction [9, 11].

Classification & Segmentation

UAS Image Understand

Classification Networks: Outputs of classifica

Classes: Cow, Deer, Horses. 60 epochs, batch



Model summary: 213 layers, 7018216 par

Class Images Labels P R mAP@.5 mAP@.5

all 23 23 0.749 0.886 0.995 0.967

cow 23 10 0.644 1 0.995 0.995

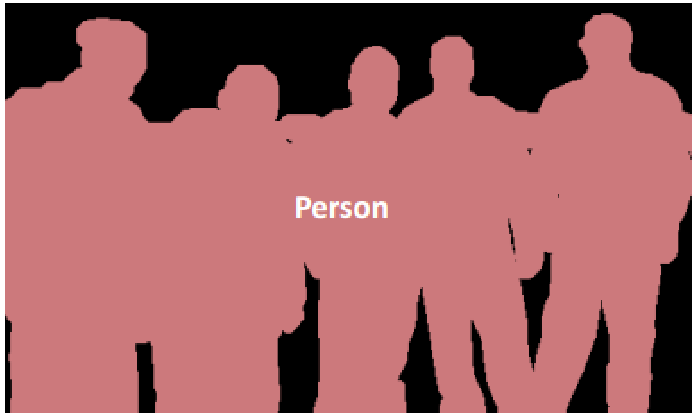
deer 23 9 0.604 1 0.995 0.995

horse 23 4 1 0.658 0.995 0.91

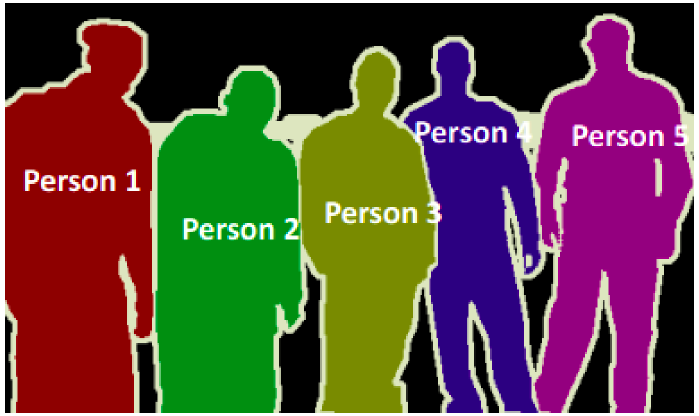
UAS Image Understanding --- Classifier outputs

Segmentation

Object Detection



Semantic Segmentation



Instance Segmentation

http://kaiminghe.com/iccv17tutorial/maskrcnn_iccv2017_tutorial_kaiminghe.pdf ---K He, Mask RCNN Tutorial from ICCV'17

UNet Outputs (Decoy – vs - Real)

UAS Image Understanding --- Summary

Environment/ Background

Occlusions

NO Distinguishing features

Small Object Size

Small Annotated Dataset

Study of the model’s parameters to provide intuitions about the trade-offs between acquisition settings, image resolution and the complexity of the appearance descriptors involved (Landon's & Jared's talk)

Choices for future annotations: crowd sourcing (Sathish's AWIR poster)

Data Fusion (Thermal + RGB)

Generate more Data / more Segmentation

- Questions?

- Thank you for your time!

Extensions

Counting animals

- semi-automatically localize and count animals
- Bias estimation

Tracking in Dynamic Environment

- Advantage from using a sequence of images rather than a single image
- how are we using the classification algorithms for this purpose?

More Data Augmentation - Multiple views of one object

- Difference in classification accuracy between single view classifier and multi-view classifier?

UAS Image Understanding --- Augmentation

Why bother?

Option & Result

What Next?

1. GAN
2. Meta-Learning problem --- Few-Shot learning
    1. N-way-K-Shot-classification [N~# classes, K~# training samples for each class]
    2. Meta Learning: we learn how to learn to classify given a set of training data instead of learning the training data to classify