# Recognition of Mammal Genera on Camera-Trap Images using Multi-Layer Robust Principal Component Analysis and Mixture Neural Networks

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# Content

- Motivation
- Problem
- State of the Art
- Objectives
- Methods
- Experimental Framework
- Results
- Conclusions

Figure 1: Artiodactyla Cervidae Mazama
Source: Instituto Alexander von Humboldt

# Motivation

Figure 2: Animals in the wild
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Non-invasive animal genera recognition, using computer vision and pattern recognition algorithms.

# Problem

Figure 3: Animal detection
Source: Instituto Alexander von Humboldt

Detection problem with intra class variation due to different poses. Context problems: illumination changes, dynamic background, shadows.

Detection of mammal genera from camera trap images, using computer vision and pattern recognition.

# State of the Art
# Segmentation

Figure 4: Previous works
Source: [Zhang et al., 2016]

Bag of Words, Histogram of Oriented Gradients, and graph cut energy minimization [Zhang et al., 2015]. Iterative embedded graph cut, histogram of oriented gradient, and convolutional neural networks [Zhang et al., 2016].

# State of the Art (2)
# Classification

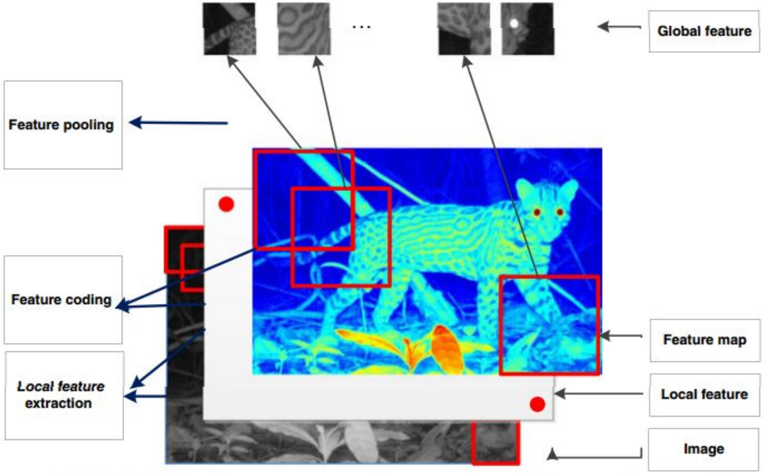


Figure 5: Previous works
Source: [Yu et al., 2013]

Dense Scale Invariant Feature Transform and cell-structured Local Binary Pattern with multi-class SVM to classify the features [Yu et al., 2013]. Convolutional Neural Networks (CNN) [Chen et al., 2014]. Deep CNN [Gomez et al., 2017].

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# Objectives

**General Objective**

- Classification of mammal genera on camera-trap images using Convolutional Neural Networks to help in conservation tasks.

**Specific Objectives**

- Design of experiments with segmentation algorithms to segment the animals in the database.
- Validation of the segmentation algorithm applied on camera-trap images.
- Design of experiments with Deep Learning architectures to separate mammal genera.
- Validation of the Deep Learning architectures applied on camera-trap images.

# Methods
# Multi-Layer RPCA

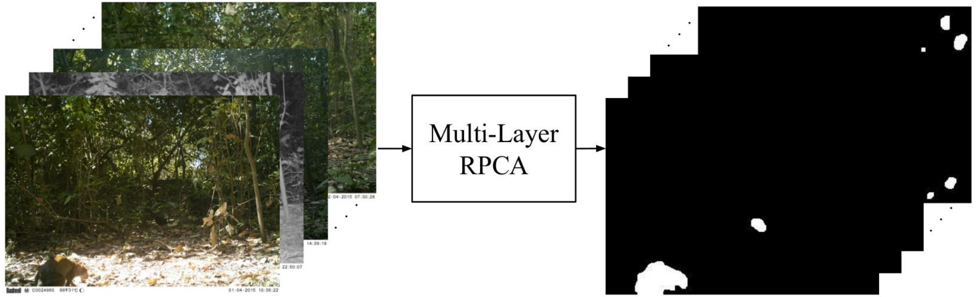


Figure 6: Segmentation algorithm, Multi-Layer Robust Principal Component Analysis (Multi-Layer RPCA)

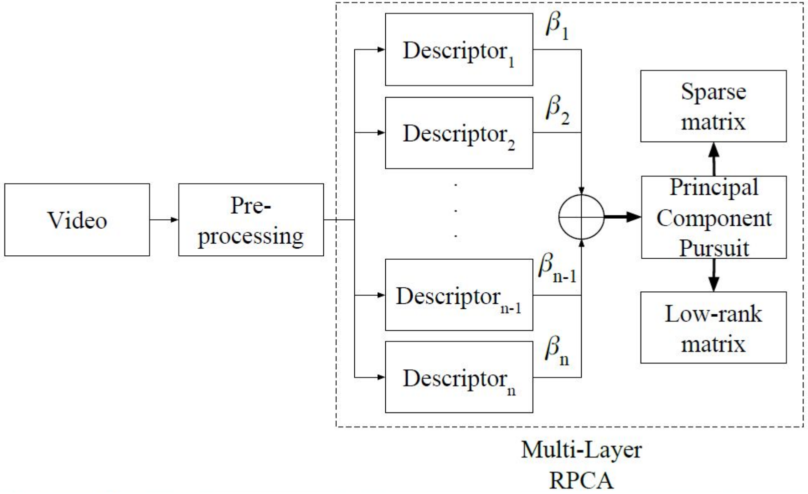


Figure 7: Multi-Layer RPCA method

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# Methods (3)
# CNN

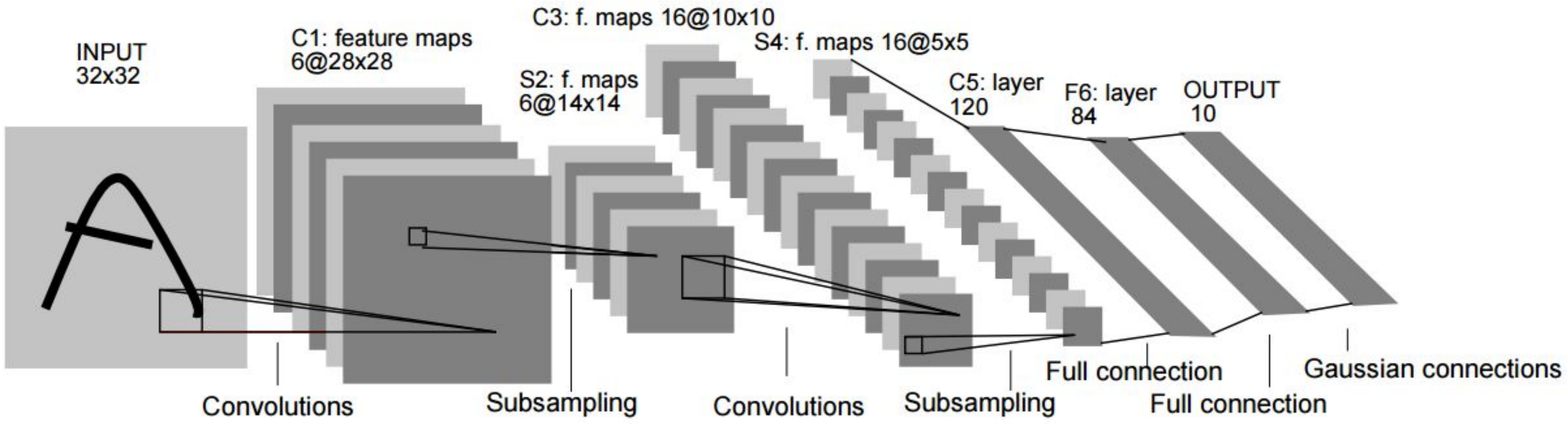


Figure 8: Convolutional Neural Network (LeNet) [LeCun et al., 1998]

# Methods (4)
# MixtureNet

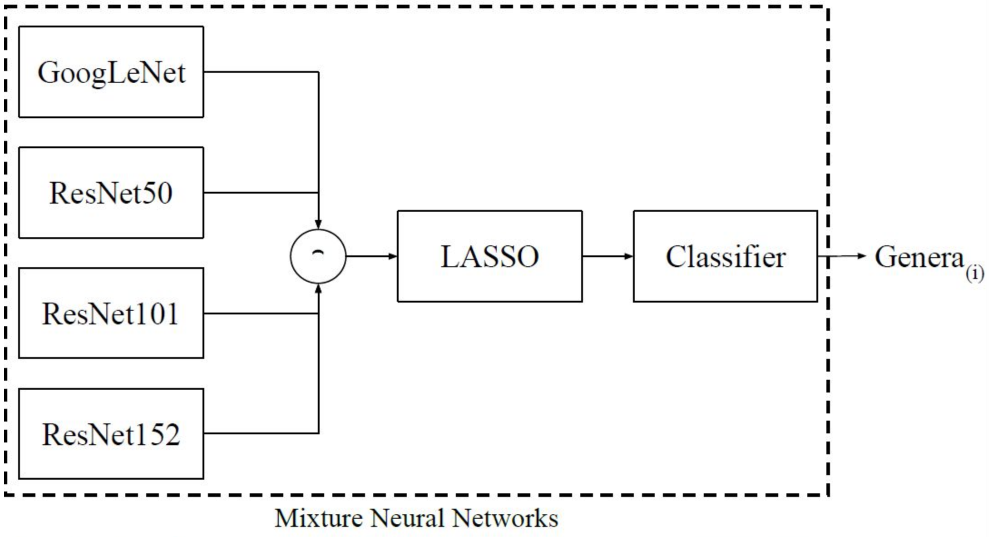


Figure 9: MixtureNet

CNN: GoogLeNet [Szegedy et al., 2015], ResNet50, ResNet101, y ResNet152 [He et al., 2016]. Least Absolute Shrinkage and Selection Operator (LASSO) [Tibshirani, 1996].

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# Methods (5)

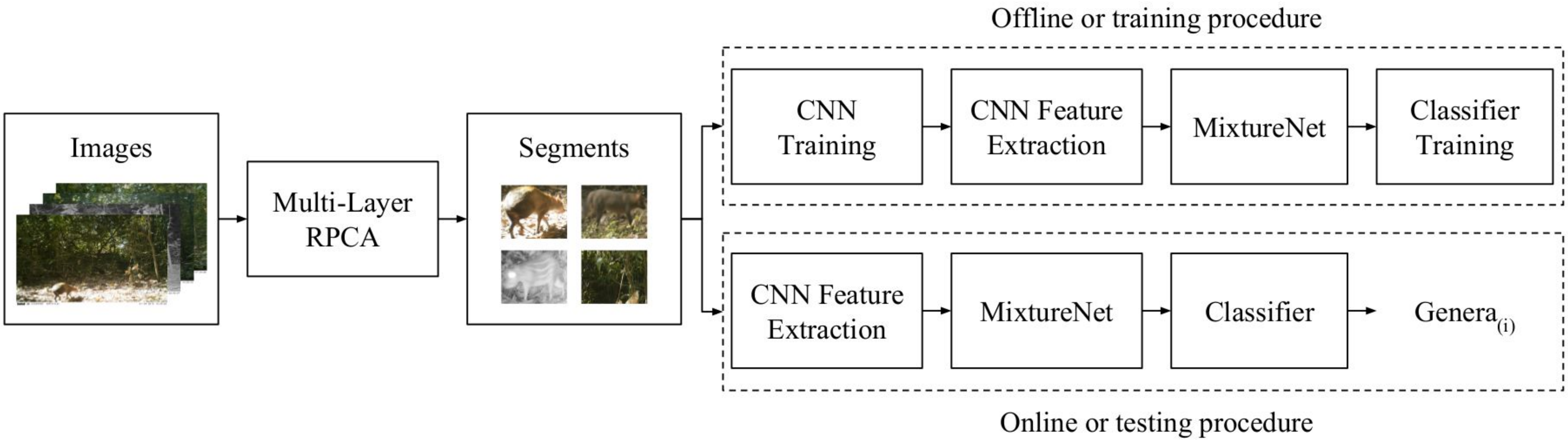


Figure 10: Pipeline of the mammal classification method presented in this work

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# Experimental Framework
# Database Segmentation

Figure 11: Ground Truth images

The database consists of 1065 images from 30 color and infrared sequences. The length of each sequence data set varies from 9 to 72 images, depending on the animal activity in that sequence. We randomly chose the 60 sequences, ensuring animal activity in each sequence. Each image of the database has a Ground Truth.

# Experimental Framework (2)
# Database

Figure 12: Dasyprocta (4228, 3396), Mazama (441, 292), Pecari (712, 343), Cerdocyon (288, 167), Leopardus (284, 207), Dasypus (741, 389), Didelphis (688, 207), Proechimys (472, 229), Cuniculus (1150, 883), Tamandua (204, 125)

# Experimental Framework (3)
# Metrics

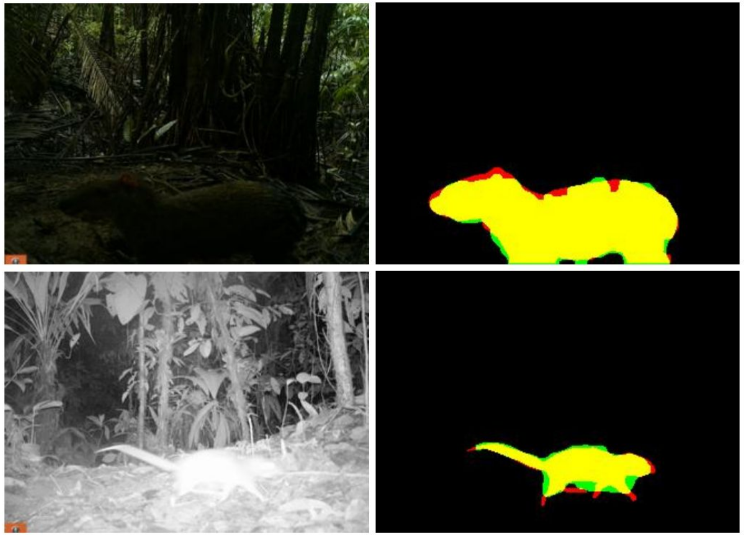

Figure 13: Extracting f-measure

Segmentation:

- F-measure per sequence.
- Average f-measure.

Classification:

- Accuracy.
- Kappa index (our classification method against a random classifier).

# Experimental Framework (4)
# Experiments

Segmentation:

- Multi-Layer RPCA with 2 descriptors and exhaustive search of the $\beta$ parameter with 7 Principal Component Pursuit algorithms of the state-of-the-art.
  - Color, infrared, and color & infrared sequences.

Classification:

- Classification with expert segmentation (10 genera categories).
- Classification using automatic segmentation with intersection over union greater than 50% (8 genera categories and a false positive category).
  - Artificial Neural Network (ANN), Linear and Radial Basis Function Support Vector Machines (LSVM and RSVM): hyperparameters-optimization with test (optimistic results).
  - Direct evaluation of CNNs on test (non-optimistic results), without LASSO.

# Results
## Segmentation

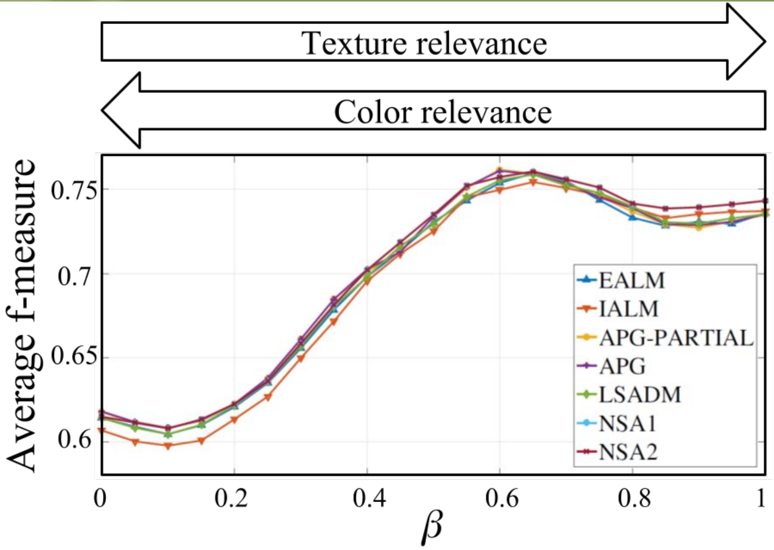


Figure 14: Results with color images

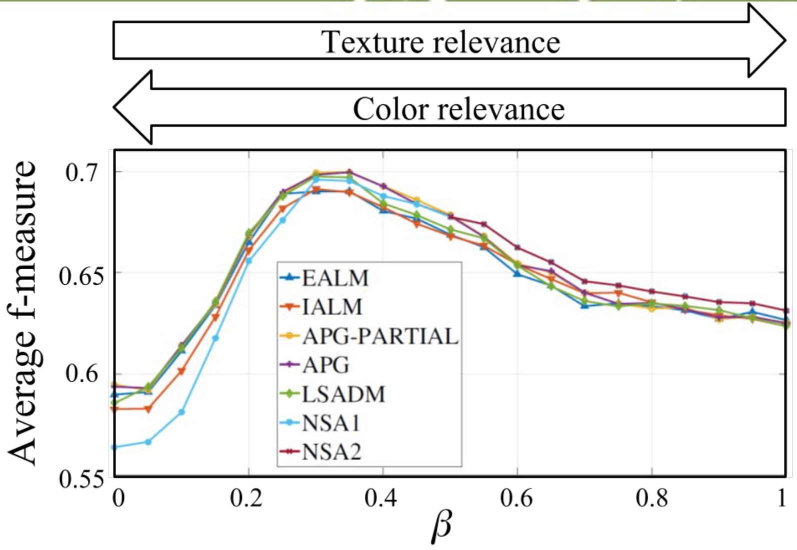


Figure 15: Results with infrared images

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# Results (2)
# Segmentation

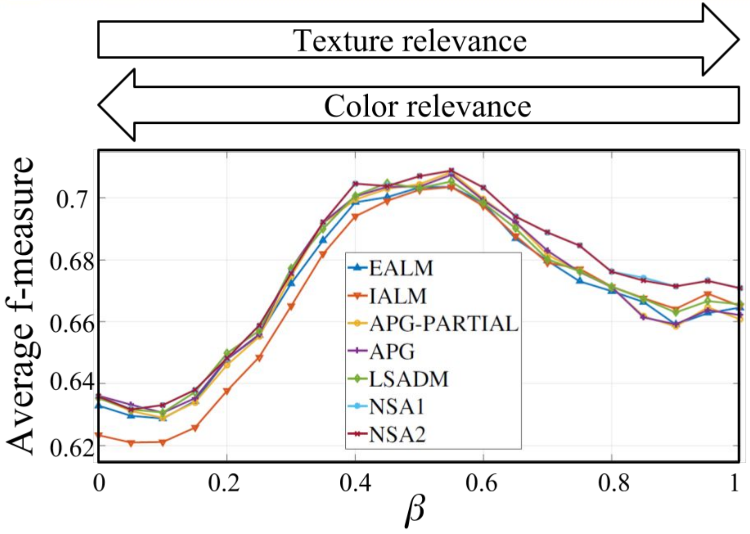


Figure 16: Results with color and infrared images

| Experiment | Algorithm | $\beta$ | Avg F-measure |
|---|---|---|---|
| Color images | APG-PARTIAL | 0,6 | 0,7617 |
| Infrared images | APG-PARTIAL | 0,35 | 0,6997 |
| Color & Infrared images | NSA2 | 0,55 | 0,7088 |

Table 1: Summary of the results

# Results (3)
# Classification (optimistic results)

| CNN | Accuracy [%] | | | Accuracy LASSO [%] | | | Kappa |
|---|---|---|---|---|---|---|---|
| | ANN | LSVM | RSVM | ANN | LSVM | RSVM | |
| GoogLeNet | 10 | 10 | 10 | 86,72 | 10 | 85,74 | 0,8525 |
| ResNet50 | 88,85 | 1,15 | 88,36 | 86,39 | 10 | 85,41 | 0,8761 |
| ResNet101 | 90,49 | 89,34 | 89,34 | 87,87 | 86,39 | 86,89 | 0,8944 |
| ResNet152 | 90,66 | 89,51 | 90,16 | 89,67 | 88,52 | 88,85 | 0,8962 |
| MixtureNet | 10 | 10 | 10 | 89,67 | 10 | 87,87 | 0,8852 |
| MixtureResNet | **90,82** | 84,59 | 87,7 | 89,34 | 10 | 87,7 | 0,898 |

Table 2: Results using expert segmentation

| CNN | Accuracy [%] | | | Accuracy LASSO [%] | | | Kappa |
|---|---|---|---|---|---|---|---|
| | ANN | LSVM | RSVM | ANN | LSVM | RSVM | |
| GoogLeNet | 11,29 | 11,11 | 11,11 | 89,78 | 11,11 | 88,53 | 0,8851 |
| ResNet50 | 91,94 | 19,89 | 91,22 | 89,43 | 11,11 | 89,07 | 0,9093 |
| ResNet101 | 85,66 | 86,38 | 85,48 | 83,87 | 83,51 | 84,05 | 0,8468 |
| ResNet152 | 92,83 | 92,83 | 92,65 | 91,58 | 91,4 | 90,32 | 0,9194 |
| MixtureNet | 11,29 | 11,11 | 11,11 | 92,83 | 11,11 | 91,04 | 0,9194 |
| MixtureResNet | **94,09** | 88,53 | 86,02 | 92,83 | 11,11 | 91,58 | 0,9335 |

Table 3: Results with automatic segmentation and false positive class

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# Results (4)
# Classification (non-optimistic results)

| Redes | Accuracy [%] | Kappa index | CNN time training (600,000 iterations) |
|---|---|---|---|
| GoogLeNet | 84,59 | 0,8288 | 2 days, 26 minutes |
| ResNet50 | 88,2 | 0,8689 | 3 days, 15 hours, 52 minutes |
| ResNet101 | **88,85** | 0,8761 | 3 days, 13 hours, 33 minutes |
| ResNet152 | **88,85** | 0,8761 | 3 days, 11 hours, 54 minutes |

Table 4: Results using expert segmentation, direct evaluation of the CNNs

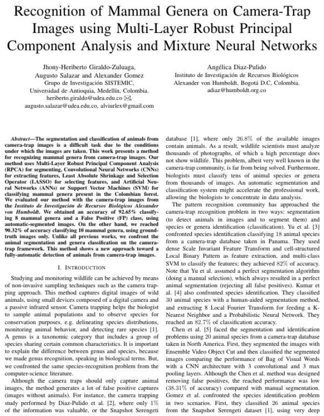
| Redes | Accuracy [%] | Kappa index | CNN time training (600,000 iterations) |
|---|---|---|---|
| GoogLeNet | 88,17 | 0,8669 | 1 day, 23 hours, 28 minutes |
| ResNet50 | 90,32 | 0,8911 | 3 days, 14 hours, 55 minutes |
| ResNet101 | 85,48 | 0,8367 | 3 days, 12 hours, 52 minutes |
| ResNet152 | **91,94** | 90,93 | 3 days, 11 hours, 47 minutes |

Table 5: Results with automatic segmentation and false positive class, direct evaluation of the CNNs

# Conclusions

- Multi-Layer RPCA can handle the dynamic background of the camera-trap images.
- LASSO selection make the method more robust against bad features.
- LASSO selection is useful for combining CNNs (trained separately), when any CNN has harmful features. In another way, the MixtureNet inherits the harmful features of each CNN.
- Although the Multi-Layer RPCA generates thousands of false positives, the CNNs can handle this problem.
- The MixtureResNet exhibits the best kappa indexes in both classification experiments.
- The classification method fails in images with two or more challenges (e.g. overexposed and partially-occluded images).
- We tested images with IoU $> 0.5$ and IoU $= 0$ for animals and False Positives, respectively. Certainly, regions with $0 <$ IoU $\leq 0.5$ are limitations of our method.

# Publications



Recognition of Mammal Genera on Camera-Trap Images using Multi-Layer Robust Principal Component Analysis and Mixture Neural Networks

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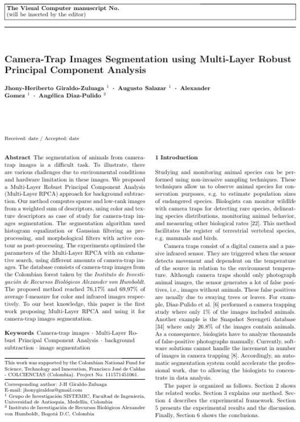
Conference: IEEE International Conference on Tools with Artificial Intelligence 2017
Hindex: 28 (Scimago)



The Visual Computer manuscript No.
(will be inserted by the editor)

Camera-Trap Images Segmentation using Multi-Layer Robust Principal Component Analysis

Jhony-Heriberto Giraldo-Zuluaga [1] · Augusto Salazar [1] · Alexander Gomez [1] · Angélica Diaz-Pulido [2]

Received: date / Accepted: date

Journal: Visual Computer
Quartile: Q2, A2 (Colciencias)
Hindex: 53 (Scimago)

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# To do

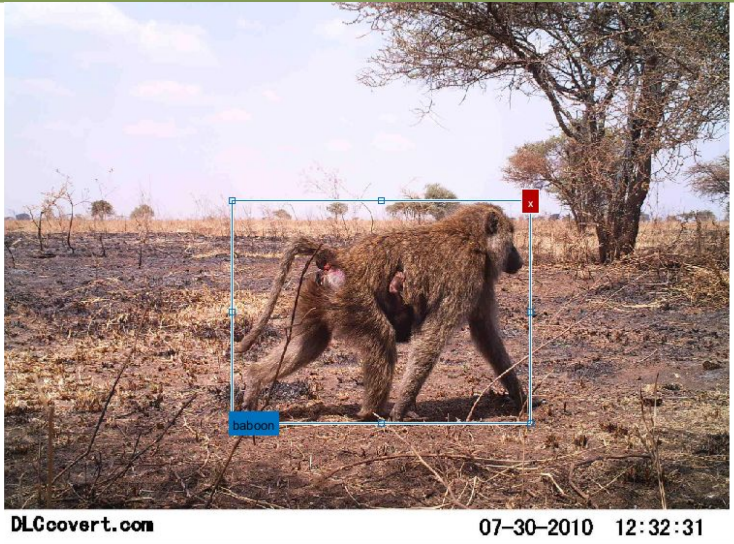


Figure 17: Snapshot Serengeti
Source: [Swanson et al., 2015]

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Thanks.
Questions?

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# Attachments

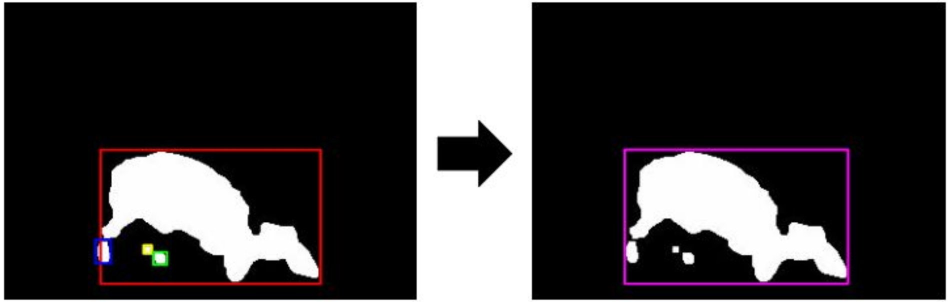
Recall : TP / (TP + FN)

Precision : TP / (TP + FP)

F-Measure : (2 * Precision * Recall) / (Precision + Recall)

$$\begin{aligned} &\text{minimize} && ||\boldsymbol{L}||_* + \lambda||\boldsymbol{S}||_1 \\ &\text{subject to} && \boldsymbol{L} + \boldsymbol{S} = \boldsymbol{M}. \end{aligned}$$

$$IoU = \frac{A_{pred} \cap A_{gt}}{A_{pred} \cup A_{gt}}$$



$$\min_{\alpha_0, \boldsymbol{\alpha}} \left( \frac{1}{2N} \sum_{i=1}^{N} (y_i - \alpha_0 - \boldsymbol{x}_i^T \boldsymbol{\alpha})^2 + \gamma \sum_{j=1}^{p} |\alpha_j| \right)$$

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