Towards landmarks prediction with Deep Network

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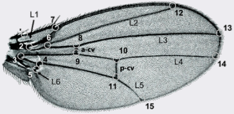
Context

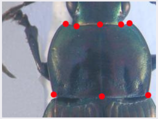
Morphometry analysis

- Used to study the complex interaction between the evolution of insect and environmental factors.
- Characterize the common information of biological shape, such as, shape, sizes, or **landmarks**,. . . .

Landmark

- A kind of **point of interest**
- A specific point defined by biologist. For example, intersection of veins on fly wing, the corner of beetle's pronotum,. . .

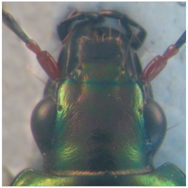




Dataset

- Images have been taken from 293 **beetles**, seperate into 5 parts (images),
- Format: 2D in RGB color,
- Focus on **pronotum** images.

(a) Body part

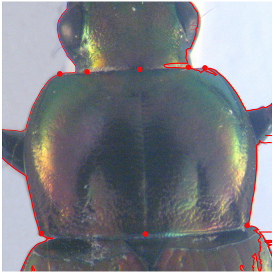


(b) Head part

Problems

Pronotum image:

- Very noise: it connects to a part of head and body
- Difficult to segment the object
- The landmarks stay both on the shape and inside the object



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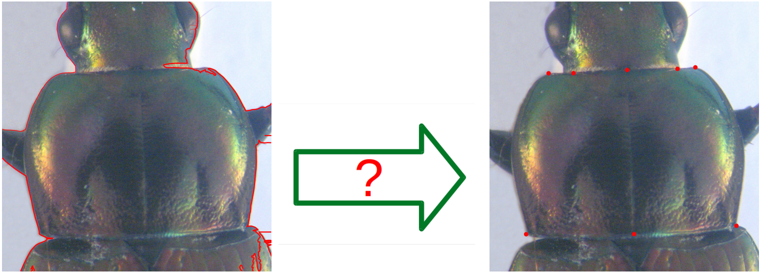

How to automatically predict the landmarks coordinates on pronotum images?

Content

Deep learning and Convolutional Neural Networks
- Deep learning
- Convolutional neural networks (CNNs)

Proposed method
- Network architectures
- Data augmentation

Results
- Training from scratch
- Fine-tuning

Conclusion

Deep learning

Definition[1]

- A class of machine learning methods,
- Use a cascade of multiple layers for feature extraction and transformation,
- Learn multiple levels of representation in supervised or unsupervised.

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015

Deep learning

Definition[1]

- A class of machine learning methods,
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- Learn multiple levels of representation in supervised or unsupervised.

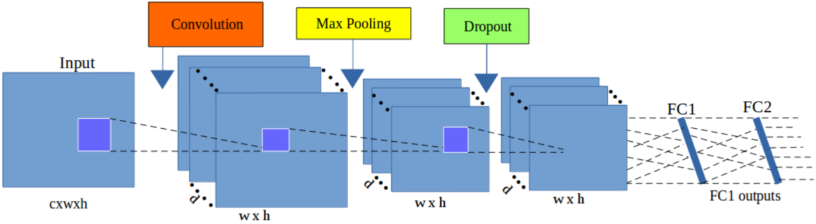
Applications[1]

- Computer vision (image recognition and classification)
- Speech recognition
- Question answering, language translation

[1] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015

Convolutional neural networks

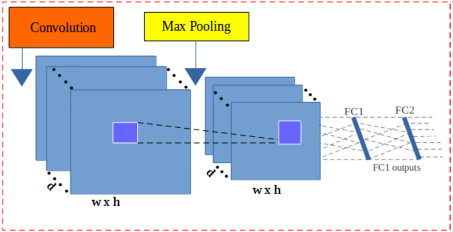
- Consists an input, an output and multiple hidden layers[1]
- Arranges the data in 3 dimensions: *width, height and depth*
- Classical layers: convolutional layers (**CONV**), pooling layers (**POOLING**), dropout layers (**DROPOUT**), full-connected layers (**FC**), ...



[1] Y. LeCun et al, "Convolutional networks and applications in vision", 2010.

Elementary block:

- A **CONV** layer,
- A **maxixum POOLING** layer,



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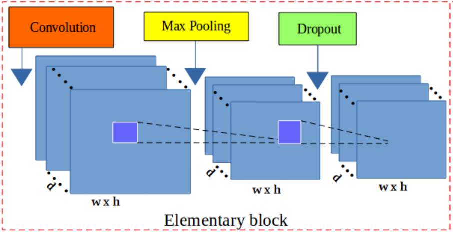
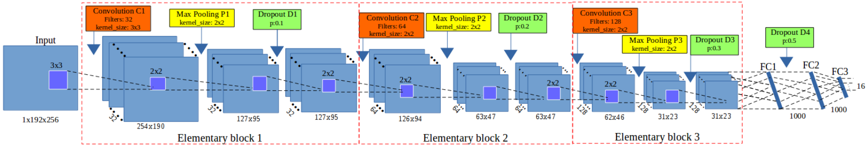


Our proposed architecture

Elementary blocks composition

The proposed model:

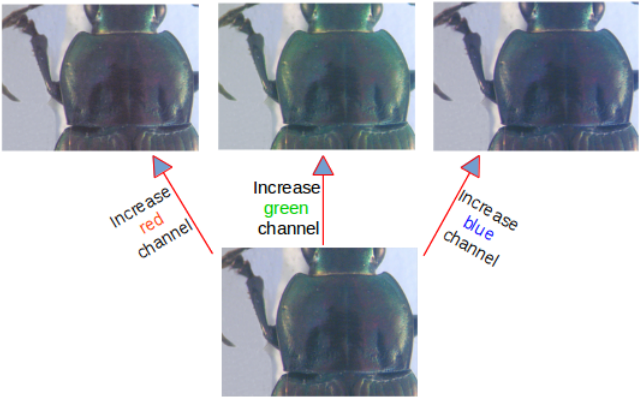
- **Three** elementary blocks,
- **Three** full-connected (FC) layers
- A dropout layer was inserted between the first of two FCs



Data augmentation

Dataset: 293 pronotum images in RGB format.
Augmentation methods:

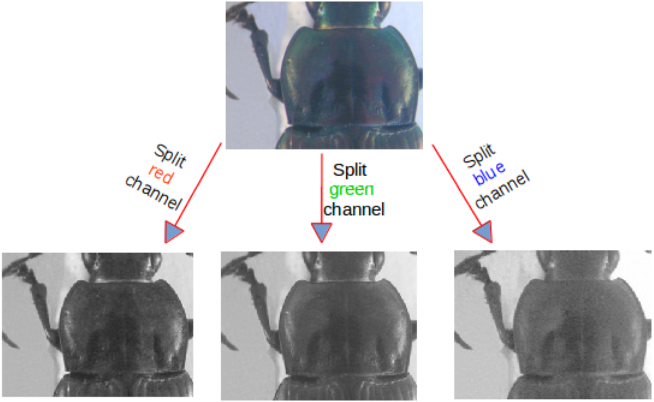
- Increase the value of each channel,



Data augmentation

Dataset: 293 pronotum images in RGB format.
Augmentation methods:

- Split the channels.



Data augmentation

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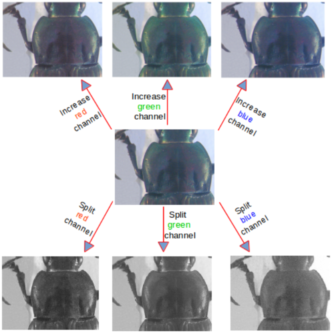
Augmentation methods:

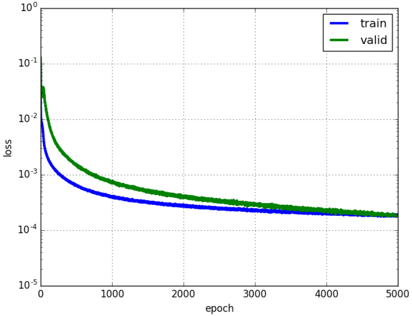
- Increase the value of each channel,
- Split the channels.

Total: $293 \times 7 = 2,051$ images



Training

- Training dataset: $1,820$ images (260×7)
- Apply the cross-validation to select the tranining data
- Training parameters: momentum ($0.9 \rightarrow 0.9999$), learning rate ($0.03 \rightarrow 0.00001$), 5000 epochs[1]
- Image shows training and validation losses of the model. Blue curve is training loss, green curve is validation loss.
- Training time: 3 hours using NVIDIA TITAN X card.



First result
Correlation metrics and landmarks on the images

- Quality metrics: coefficient of determination (r^2), explained variance (EV), Pearson correlation.

Metric	**r^2**	**EV**	**Pearson**
Proposed architecture	**0.9952**	**0.9951**	**0.9974**

First result

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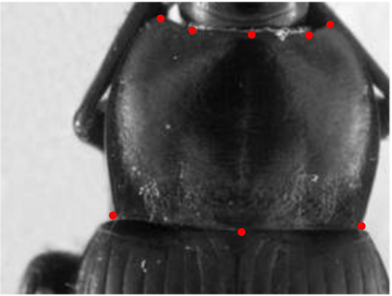
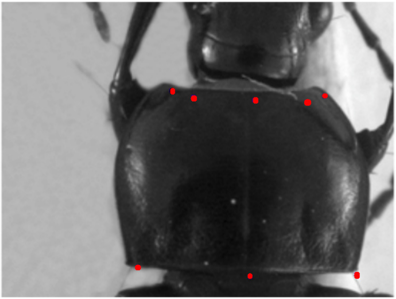
- Quality metrics: coefficient of determination (r^2), explained variance (EV), Pearson correlation.

Metric	r^2	EV	Pearson
Proposed architecture	**0.9952**	**0.9951**	**0.9974**

- Display the landmarks on the images:



(a)



(b)

First result
Average distances

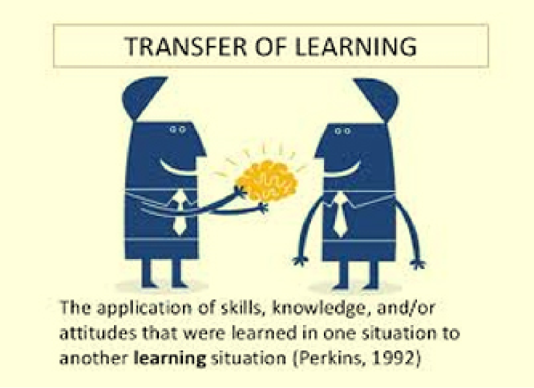
- Calculate the distance between predicted landmarks and corresponding manual landmarks.
- Compute the average distance by landmark.

Landmark	**Distance** (in pixels)
1	**4.002**
2	4.4831
3	4.2959
4	4.3865
5	4.2925
6	**5.3631**
7	4.636
8	4.9363

The statistic of average distances on all images per landmark.

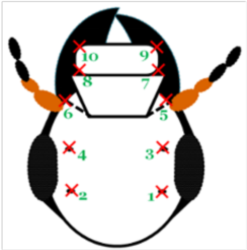
Transfer learning

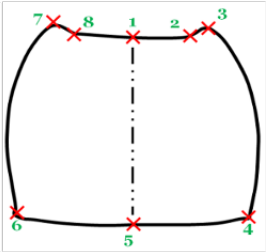
- Re-uses model developed for a specific task/dataset to lead another task with another dataset
- **Fine-tuning**: retrain a pretrained model
- **Model Zoo** (Caffe library): people share their network weights.

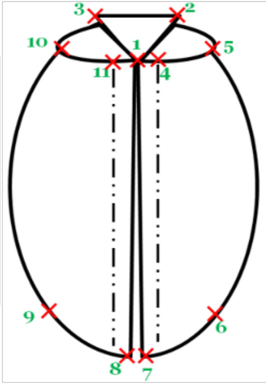


Fine-tuning our model

- Fine-tuning pronotum images on **VGG-16, VGG-19, ResNet50** is not precise
- Train the model on a dataset including the images of 3 parts of beetles : head, body and pronotum parts
- Fine-tune pretrained model on pronotum dataset







Fine-tuning our model

- Fine-tuning pronotum images on **VGG-16, VGG-19, ResNet50** is not precise
- Train the model on a dataset including the images of 3 parts of beetles **(5, 460 images)**: head, body and pronotum parts
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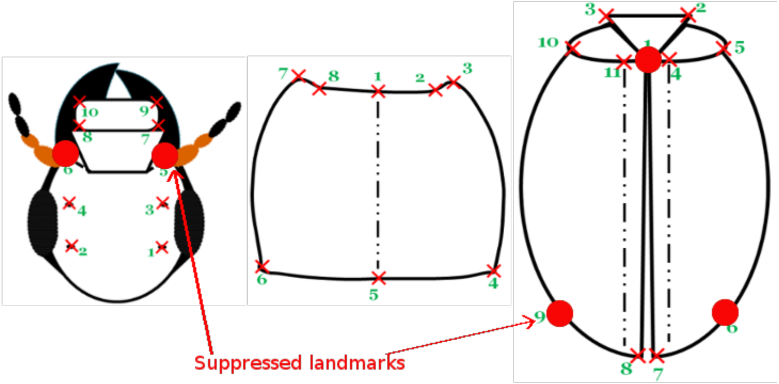
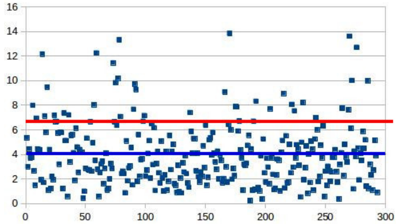


Comparing the average distances between two processes (training from scratch and fine-tuning).

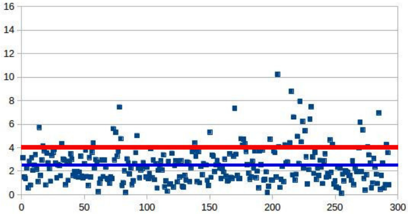
Landmark	From scratch		With fine-tuning	
	Average	SD	Average	SD
LM1	**4.002**	**2.5732**	**2.486**	**1.5448**
LM2	4.4831	2.7583	2.7198	1.7822
LM3	4.2959	2.7067	2.6523	1.8386
LM4	4.3865	3.0563	2.7709	1.9483
LM5	4.2925	2.9086	2.4872	1.6235
LM6	**5.3631**	**3.4234**	**3.0492**	**1.991**
LM7	4.636	2.8426	2.6836	1.7781
LM8	4.9363	3.0801	2.8709	1.9662

Results
Distribution of average distances

- The distribution of distance of the best result (1^{st} landmark)

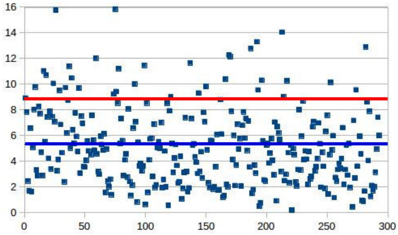


(a) Training from scratch



(b) With fine-tuning

- The distribution of distance of the worst result (6^{th} landmark)



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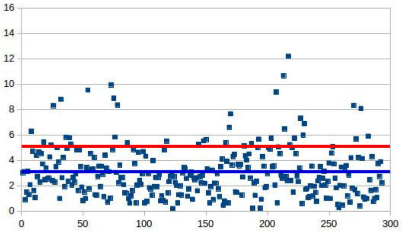

(b) With fine-tuning

Conclusion

- Propose a CNN to predict the landmarks on pronotum images.
- Propose procedure to augment the dataset.
- Apply fine-tuning to improve the quality of predicted landmarks.
- The predicted landmarks able to replace the manual landmarks without segmentation step.

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Future works

- Applying the method on body and head parts
- Going deeply how to design the right pre-training set

Thank you for attention!