Landmarks detection by convolutional neural network

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***Abstract*—Morphometric analysis is general method applied to organisms and used to appreciate the covariances between the ecological factors and the organisms(shape, size, form,...). In which, landmark-based morphometry is known as one of the approaches to analyze the characteristics of organisms. Finding enough the landmarks can give to biologist a comprehensive description of organism. In this study, we propose a convolutional neural network (CNN) to predict the landmarks on beetle images. The network is designed as a pipeline of layers, it was trained with a set of manually landmarks dataset. Then, the network is used to provide the morphometric landmarks on biological images automatically. The coordinates of predicted landmarks are evaluated by calculating the correlation coefficient with the manual coordinates which given by the biologists. Besides, the evaluations of the distances between predicted and manual landmarks are also given. The network is implemented by Python on Lasagne framework.**

***Index Terms*—Morphometry, biological, landmarks, CNN**

I. Introduction

Morphometry analysis refers to measure the topography of an object, a notion that includes the shape and size. Morphometry analysis is often applied to biological organisms. Biologists work with several parameters from organisms such as lengths, widths, masses, angles,... to analyze the interaction of environment with organisms. Besides the traditional information, landmarks (or points of interest in the image) are known as one of the characteristics to analyze the shape. Instead of collecting all information, the shape is determined by a finite set of points, called landmarks. The landmarks are the points that store the important information about the shape of the object, *for example*, the corners of the human mouth are a kind of landmarks. Currently, the landmarks are along the outline of the object but in some special cases, it has been defined inside the object. Morphometry landmarks are a kind of points-of-interest, they are directly linked to the animal anatomy. In our study, the morphometric landmarks are specific points defined by the biologists. They are used in many biological studies. Manual landmarks setting is time-consuming and difficult to reproduce. Therefore, a method that gives automatically the location of landmarks could has a lot of interest.

This work introduces a method for automatic detection of the landmarks on biological images. The main idea consists design and train a convolutional neural network[1] with a set of manual landmarks. By this way, the trained network will be able to detect the morphometry landmarks on biological images. The dataset includes 293 beetles images from Brittany lands. All the images are presented in RGB color with two dimensions. For each beetle, the biologists took images of five parts: *left and right mandibles, head, body, and pronotum*. For each image, a set of landmarks has been manually determined by experts. In the last our work, a method has been presented to determine the landmarks on left and right mandibles[2]. This method is based on the image processing techniques[3], combining with principal component analysis[4] and SIFT descriptor[5]. In the context of this work, we work on the dataset of pronotum images. For each pronotum image, a set of 8 manual landmarks have been set by the biologists. The coordinates of manual landmarks were used as the input to train the network. During the first phase, a number of 260 images and their manual landmarks were used to train and validate the network. The remaining images were used to evaluate the output model of the network in the second phase.

In the next section, we study several related works to determine the landmarks on 2D images by CNN. In section 3, we present an overview about convolutional neural networks. Section 4 presents the architecture of the network, its parameters, and the implementation. All the experiments and analysing the results will be detailed in section 5.

II. Related works

Landmark or point of interest is a specific point that may contain the useful information. For example, the tip of the nose or the corners of the mouth are landmarks on human face. Lowe et al[5] have proposed SIFT method to find the corresponding keypoints between two images. This method is composed by four steps: (1) scalespace extrema detection, (2) keypoint localization, (3) orientation assignment, and (4) keypoint descriptor. It examed the images at all scales and orientation of the input images.

Palaniswamy et al[6] have proposed a method to automatically locate the landmarks in digital images of Drosophila wings. This method used a reference image with its landmarks and found the landmarks on another image. Firstly, it studied the feature structure of the wings; secondly, the descriptors

of the compact invariants have been recored; finally, the landmarks are located and correlation-based to verify the location of estimated landmarks.

In recent years, deep learning is known as a solution in computer vision. Using convolutional network to determine the landmarks on 2D images have achieved better results. Yi Sun et al.[7] have proposed cascaded convolutional neural networks to predict the facial points on the human face: *left eye center, right eye center, nose, left mouth corner, and right mouth corner*. The cascade convolutional neural networks are separated into three levels. In the first level, the networks are designed to predict several landmarks together by covering the whole face; the networks in the second and the third level are used to predict each landmark on the face. They take the patches centered at the predicted positions of previous levels as input and try to improve the accuracy of predicted positions. Zhanpeng Zhang et al[8] proposed a *Tasks-Constrained Deep Convolutional Network* to optimize facial landmarks detection. The model determines the facial landmarks with a set of related tasks such as head pose estimation, gender classification, age estimation, face recognition, or facial attribute inference. Firstly, all the images are used as the input, their output spaces the images into several tasks. Then, the network is applied to determine the landmarks on the images of each task. In biology field, Cintas et al[9] has introduced a network to predict the landmarks on human ears. After training, the network has the ability to predict 45 landmarks on human ears. In their proposed architecture, the network with three times repeated of a structure includes two convolutional layers with the filters, followed by maximum pooling and dropout layers. The structures then adding two full-connected layers and a dropout layer. At the end, an output layer with 90 output units corresponding with 45 landmarks is hired to provide the position of the predicted landmarks.

III. Convolutional neural networks

Deep learning allows computational model composed of multiple processing layers to learn representations of data with multiple levels of abstraction[10]. Each layer extracts the representation of the input data from the previous layer and computes a new representation for the next layer. In the hierarchy of model, higher layers of representation enlarge aspects of the input that is important for discrimination and suppress irrelevant variations. Each level of representations is corresponding to the different level of abstraction. Almost the algorithms in deep learning learn are supervised (i.e classification) or unsupervised (i.e pattern analysis) practices. During training, it uses the forms of gradient descent to update the learnable parameters via backpropagation. The development of deep learning opens the promise results of the artificial intelligent on hight dimensional data, therefore applicable to many domains: image recognition and classification[11]–[13], speech recognition[14]–[16], question answering[17] and language translation[18][19].

Convolutional neural networks (CNNs) contribute to resolve the state of the art in many computer vision such as classification[11][12] or recognition[20][21]. Normally, a CNN consists a number of connected layers. The layers of CNN has neurons arranged in three dimensions: *width, height, and depth* with learnable parameters. Fig.1 shows a common example of CNN. It is a pipeline of usual layers: convolutional layers(CONV), pooling layers(POOLING), dropout layers(DROPOUT), and full-connected layers(FC).

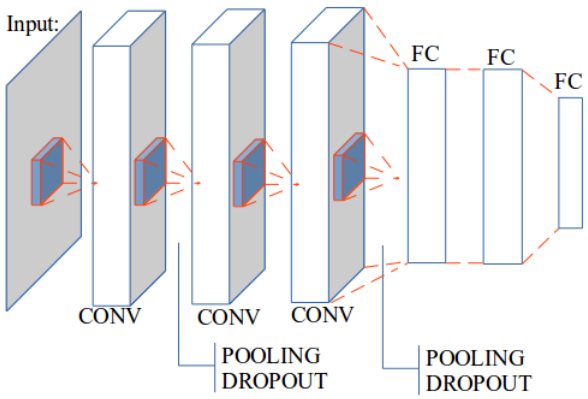


Fig. 1: An example of usual convolutional neural network

Convolutional layer computes a dot product between their weights and a small region in the input. At the output, the results of connected local regions are combined. Convolution layer uses a set of learnable filters as parameters. Each filter is small spatially but extends the depth of the input. *Pooling* layer usage to down-sampling the input, reduce the computational cost in remaining layers, and control overfit. *Dropout* layer refers to dropping out units in the network. By dropping a unit out, we mean temporarily removing it from the network, along with all its incoming and outgoing connections. *Full connected* layer refers to the output of the network. The number outputs of the last full-connected layer are corresponding with the number of predicted values.

From the beginning of deep learning until now, many deep learning frameworks have been developed. Almost the framework was served a specific aim and was open source. According to the written programming languages, the frameworks can be separated into two main groups: C++, *such as Caffe, Deeplearning4j, Microsoft Cognitive Toolkit* and Python *i.e Keras, Theano, PyTorch*.

Theano is an open source developed by machine learning group at the University of $Montréal$. It is a Python library that allows to define, optimize and evaluate mathematical expressions relating multi-dimensional arrays efficiently by using a Numpy package. Theano supports compiled on either CPU or GPU architectures. Lasagne[22] is a lightweight library in Theano. It allows to build and train the neural networks. In this work, we have used Lasagne to implement the proposed neural network.

IV. Application to landmarks identification

In previous sections, we have had an overview of the landmarks and CNN. In this section, we describe the designing

processes of the model. We have also presented the data preprocessing, training and evaluating the model.

A. Preprocessing data

The images come from a collection of 293 beetles from Brittany lands. All the images are taken with the same camera under same conditions with a 3264×2448 resolutions. For each specific part, a set of manual landmarks has been determined by biologists, *for examples, 8 landmarks for pronotum, 16 landmarks for the left mandible, 18 landmarks for right mandible*. In the content of this study, we work on pronotum part of beetle. The provided dataset contains 293 images, each image with 8 landmarks provided by biologists. The dataset was split into a training set with 260 images (training and validation) and a testing set of 33 images. During the training, the network learned the information through a pair of *(image, landmarks)* in training set. At the testing phase, the image without landmarks was given to the trained network and the predicted landmarks will be given at the output. Fig.2 shows an example of pronotum image with its manual landmarks.

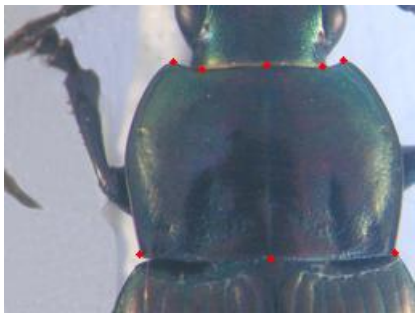


Fig. 2: An example of pronotum with manual landmarks

In some succeed networks[11][7][9], the maximum size of the inputs is not over 256 pixels. In our case, the resolution of the image is large, it becomes a difficulty for the network. During training and testing, the images are down-sampling to the new resolution of 256×192. Certainly, the landmark coordinates of the image are also scaled to suit their new resolution.

The proposed network has a large number of learnable parameters. In addition, the size of the dataset is limited, this means that overfitting will occur during the training process. Because the network works on gray-scale image and mostly the processes compute the value from the pixels. So, we have applied two rules to enlarge the size of the dataset.

The first rule was applied to change the value of each channel in the original image. According to this rule, a constant is adding to a channel of RGB image and for each time, we just change the value of one of three channels. For example, from an original RGB image, if we add a constant $c = 10$ to the red channel, we will obtain a new image with the values at red channel are greater than the red channel of original image a value of 10. By this way, we can generate three new RGB images from a RGB image.

The second rule is splitting the channels of RGB images. It means that we separate the channels of RGB into three gray-scale images. This work seems like right because the network works on single-channel images. At the end, we can generate six version from an image, the total number of images that used to train and validate is $260 \times 7 = 1820$ images (six versions and original image). The number of images that used for training and validation is split randomly by a ratio that has been set during setup the network.

In practical when we work with CNN, convergence is usually faster if the average of each input variable over the training set is close to zero. Moreover, when the input is set closed with zero, it will more suitable with the sigmoid activation function[23]. Therefore, the brightness of the image is normalized to $[0, 1]$, instead of $[0, 255]$. And, the coordinates of the landmarks are normalized to $[-1, 1]$, instead of $[0, 256]$ and $[0, 192]$ before giving to the network.

B. Network architecture and training

Three networks have been proposed and trained to perform the best architecture for automatically landmarking prediction. The networks consist on several common layers in the neural network with different learnable parameters They receive the same input of $1 \times 256 \times 192$ to train but these have different number of layers. In this section, we introduce the architectures of the networks and the process to improve the architecture from the beginning of designing.

Fig.3 shows the architecture of the first network. In this model, it has been designed in a generic method: the layers in the network are very common as the other neural networks. The network consists three repeated-structure of a convolutional layer followed by a maximum pooling layer. The deep of convolutional layers increase from $32, 64$, and 128 with different size of the filter kernel: 3×3, 2×2, and 2×2. All the kernels of pooling layers have the same size of 2×2. At the end, three full connected layers have been added to the network. The outputs of the full connected layers are $500, 500$, and 16, respectively. The output of the last full-connected layer corresponds to the number of the landmarks which we would like to predict. The training result shows that the architecture of this model is not enough good to solve the problem. It still simple and overfitting have appeared during training and validation.

The second network has the same architecture as the first one. But, number of outputs at full-connected layers have been modified from 500 to 1000 (the second model) to prevent the overfitting, but the result did not lead to better performances.

In the third network, we continued to improve the architecture of the last two models. Instead of changing the parameters, we have added four dropout layers to the network. These are considered as the good solution to prevent the overfitting. The idea of dropout is to randomly drop units from the neural network during training. It deters units from co-adapting too much. During training, dropout samples from an exponential number of different "thinned" network. At test times, it is easy to approximate the effect of averaging the prediction

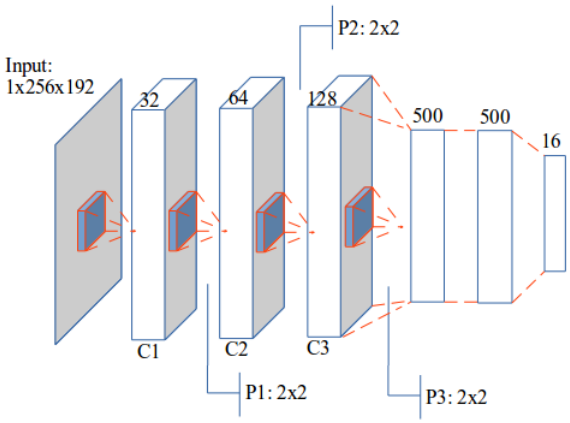


Fig. 3: The architecture of the first network

of all thinned networks by simply using a single unthinned network with smaller weights. This significantly reduces overfitting and gives major improvements over other regularization methods[24]. Fig.4 shows the architecture of the third network. The first three dropout layers are supplemented to the repeated-structures followed the maximum pooling layers. It makes the structure become the consist of a convolution layer with square filter, followed with a *maximum* pooling and dropout layer. The probability values used for dropout layers are 0.1, 0.2, and 0.3. Actually, we keep the same value for the parameters of the convolutional, pooling and full-connected layers as the second one.

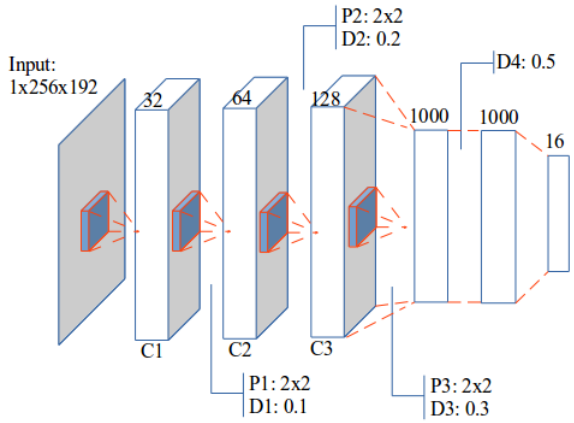


Fig. 4: The architecture of the last network

The remaining dropout layer is inserted between the first two full connected layers. The probability value of this layer is set to 0.5. The output layer still contains 16 units corresponding to the coordinates of eight predicted landmarks.

Additional, the network is designed with a small sharing learning rate and the momentum. They have been used to perform gradient descent during backward phase to update the parameters of the layers. The value of learning rate and momentum are updated over training time to fit with the remaining number of iterations. The implementation of this architecture used Python on Lasagne framework[22] which allows to train the network on GPU. The training process took around 3 hours using NVIDIA TITAN X cards. The design of the network is available on GitHub[1].

C. Results

The dataset has been built by the biologists. It includes the images and manual landmarks. So, we can use the manual landmarks coordinates as ground truth to evaluate the coordinates of predicted landmarks. In the context of deep learning, landmark prediction can see as the regression problem. Therefore, the quality metric is used to evaluate the results. In particular, we use root mean square error (RMSE) to compute the accuracy of the implemented architecture. To have the predicted coordinates of all landmarks in all the images, the network was trained many times with different training dataset and was tested on the corresponding test set.

Fig.5 and 6 show the training errors and the validation errors of a training time on the first and the third model. The blue curve presents RMSE on training set, the green curve presents the validation error. Clearly, the overfitting has appeared in the first model(Fig.5). Besides, the validation loss stabled from 2000 epochs while the training loss continued to decrease. This against with the losses of the third model. At the beginning, we see the variety between the losses but the training continue, the variety reduced and the overfitting problem have been solved.

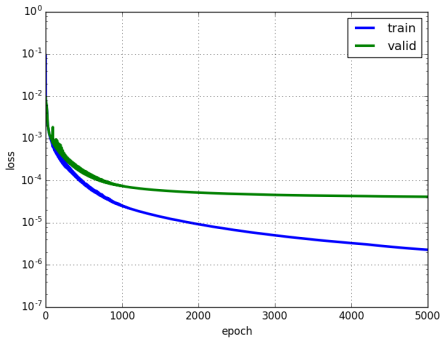


Fig. 5: Learning curves of the first model.

Fig.7 shows the predicted landmarks on unseen images in the test set by the thrid model. When we consider the distance between the predicted and manual landmarks, the accuracy of predicted landmarks on Fig.7a is 99%. The propotion on Fig.7b is 80%.

Besides following the losses of training, the distance from predicted landmarks to manual landmarks of the test images deserve attention also. Firstly, the distance between them is calculated. Then, the standard deviation[25] is used to quantify the dispersion of a set of distance. Table.I shows the average error distance given on each landmark.

Fig.8 shows the distribution of the distances on the first landmarks of all images. The accuracy based on the distance

[1]It is freely obtained by request the authors.

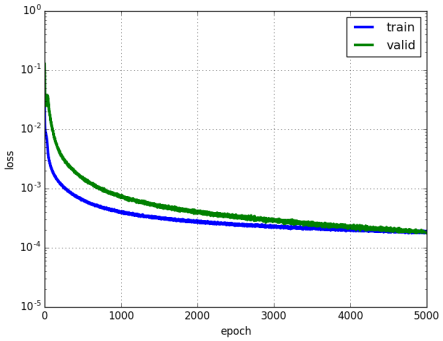
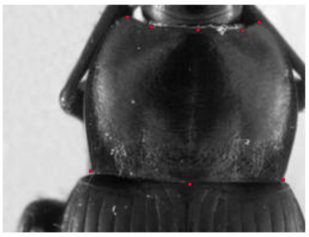
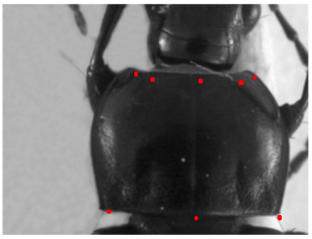


Fig. 6: Learning curves of the last model.



(a) Image with well-predicted landmarks



(b) Image with inaccuracy landmarks

Fig. 7: The predicted landmarks on an image in test set (red points)

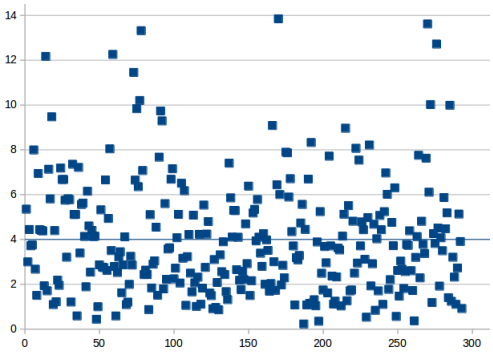


Fig. 8: The distribution of the distance on the first landmark

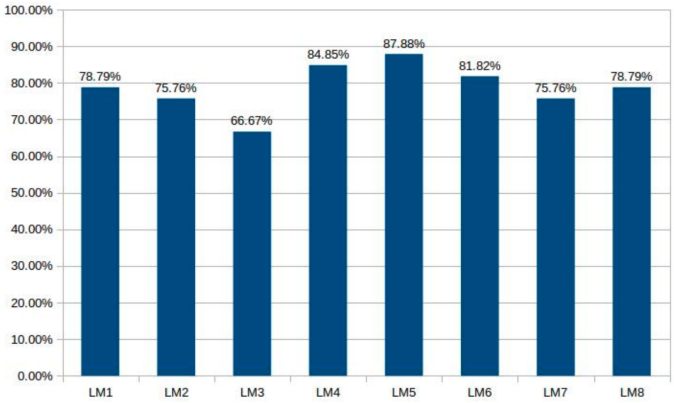


Fig. 9: The proportion of acceptable predicted landmarks

of each image can be separated into three spaces: the images have the distance less than average value: **56.66**%; the images have the distance from average value to 10 pixels: **40.27**%; and the images have the distance greater than 10 pixels: **3.07**%. The network has enabled to detect the landmark on pronotum automatically. However, the error of 10 pixels has still high in image processing.

Fig.9 shows the proportion of acceptable landmarks. In our case, a predicted landmark is acceptable if the distance between it and corresponding manual landmarks is less than the average distance plus a value of standard deviation. Most of the landmarks have been detected with the accuracy greater than 70%. However, we can see a vast difference between the correlation coefficient results and the proportions on each landmark.

At the test phase, the trained network is used to predict the landmarks on a set of unseen images (test set). With a bit of Python code, the program outputs the predicted-landmarks of the images as TPS files; in additional, it also fills and displays the predicted-landmarks on sixteenth firstly images of test data. With the outputs are TPS files, the user can use MAELab[2] framework[2] to display the landmarks on the images.

TABLE I: The average distance on each landmark

#Landmark	Distance
1	4.002
2	4.4831
3	4.2959
4	4.3865
5	4.2925
6	5.3631
7	4.636
8	4.9363

V. Conclusion and Future Works

We present a method for landmarks prediction on beetle images, specifically, pronotum images. The method used the convolutional neural network for automatic detection landmarks. It includes three times repeated of a structure consists of a convolutional layer, a max pooling layer, and a dropout layer, followed by the connected layers. During the training phase, the techniques are used to prevent overfitting, a common issue of the neural network. The network was trained in several times in different selection of training data. After training with the manual landmarks which given by the biologist, the network is possible to predict the landmarks on the set of unseen images. The model is implemented using open source tools and available on GitHub.

The results from the testing period are evaluated by calculating the distance between manual landmark and corresponding predicted-landmark. Firstly, the average of distance errors

[2]MAELab is a free software written in C++. It can be directly and freely obtained by request at the authors.

on each landmark was also considered. Then, the standard deviation based on the distance is used to correct the acceptable landmarks. The quality of prediction can be used to replace for manual landmarks in some aspect. Using the convolutional network to predict the landmarks on biological images promising the good results. However, when we expect more about the accuracy of predicted landmarks, the result of this work is not enough. Therefore, future research in landmarking identification appears as a improve the worth exploring.

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