Automated location detection of injection site for preclinical stereotactic neurosurgery through fully convolutional network

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ABSTRACT

Currently, injection sites of probes, cannula, and optic fibers in stereotactic neurosurgery are typically located manually. This step involves location estimations based on human experiences and thus introduces errors. In order to reduce location error and improve repeatability of experiments and treatments, we investigate automated methods to locate injection sites. This paper proposes convolutional neural networks to locate specific anatomical points on skulls of rodents. Experimental results show that the proposed locating framework is capable of identifying Bregma and Lambda points in the images of skulls with an average error of 500um. This method is robust to different lighting conditions and mouse orientations, and has the potential to simplify the procedure of locating injection sites.

INTRODUCTION

As shown in Fig. 1, Bregma and Lambda are two specific anatomical points on the skull to help locate injection sites in stereotactic neurosurgery [1]. Recent progresses in convolutional networks provide an promising way to identify features in images through image segmentation [2-3]. This work formulated the Bregma/Lambda locating problem as an image segmentation task, and located these points in camera images.

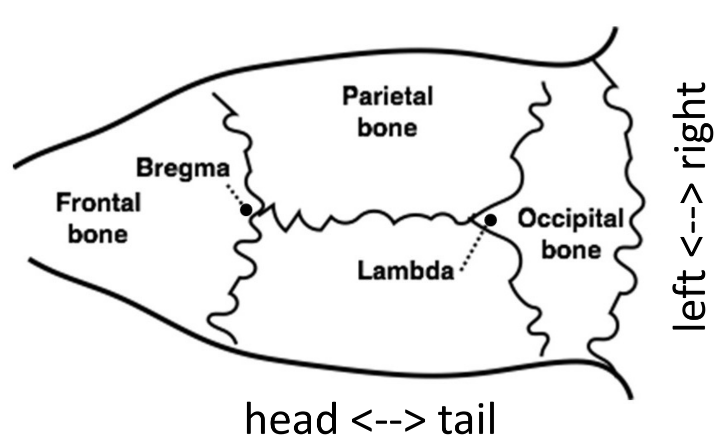

Fig. 1 Schematic of Bregma and Lambda points on rodent skull.

METHODS

Dataset

Mouse skull images were obtained from mice (male and female, age 8-28 weeks, various strains) that were previously sacrificed for other experimental purposes within 2 days. In each image, a bounding box and two points were labeled by surgeon to denote the skull area and Bregma/Lambda points.

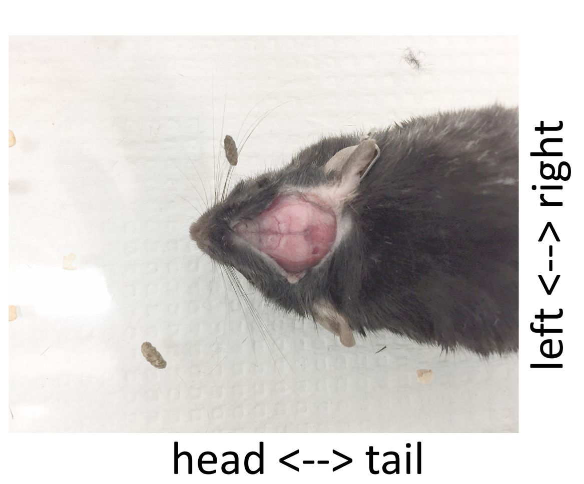

Fig. 2 Raw image of a mouse.

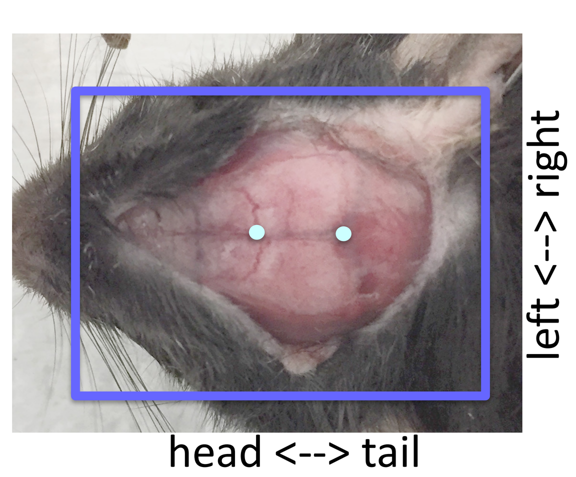

Fig. 3 The manually labeled bounding box and points on a mouse image.

METHODS (cont'd)

Bregma/Lambda locating framework (Fig. 4)

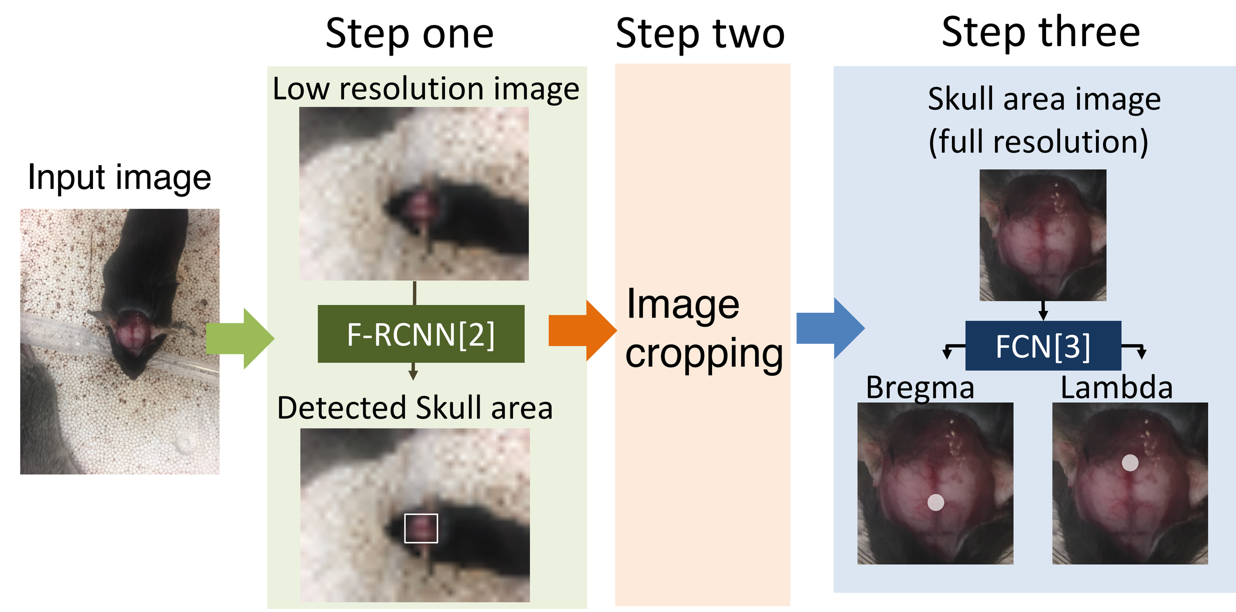

Fig. 4 Locating framework for Bregma and Lambda.

Step one Regional convolutional network (RCNN): Detect skull areas in low-resolution images. This network followed the implementation in paper [2]. With the detected skull area coordinates, the full-resolution skull area image was selected and passed to step two.

Step two Image cropping: Crop the full-resolution skull area images as inputs for step three. Three cropping methods (Fig. 5) were used, and their influences on the locating error of Bregma and Lambda were compared in the Results section.

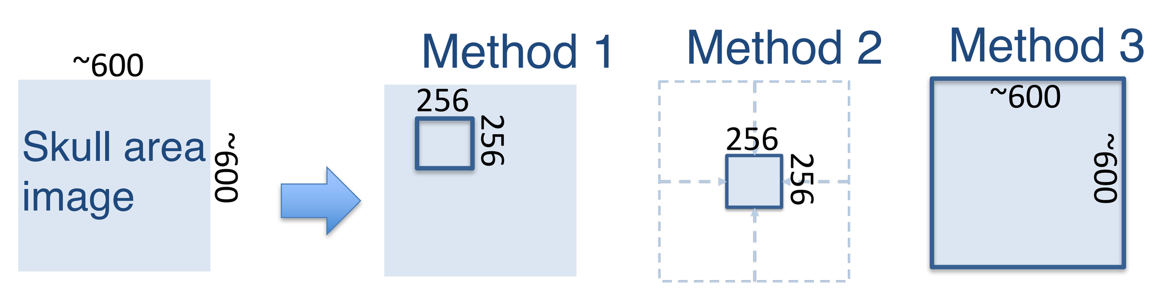

Fig. 5 Three cropping methods: *Method 1*: In training process, a subarea was randomly selected from the skull area image; in testing process, a series of subareas were generated by sliding a window across the skull area image. *Method 2*: In both training and testing process, the skull area image was down-sampled. *Method 3*: In both training and testing process, the original skull area image was used.

Step three Fully convolutional network (FCN) [3]: Segment Bregma/Lambda points from the skull area image and estimate their locations using the geometric center of the segmented regions (Fig.6).

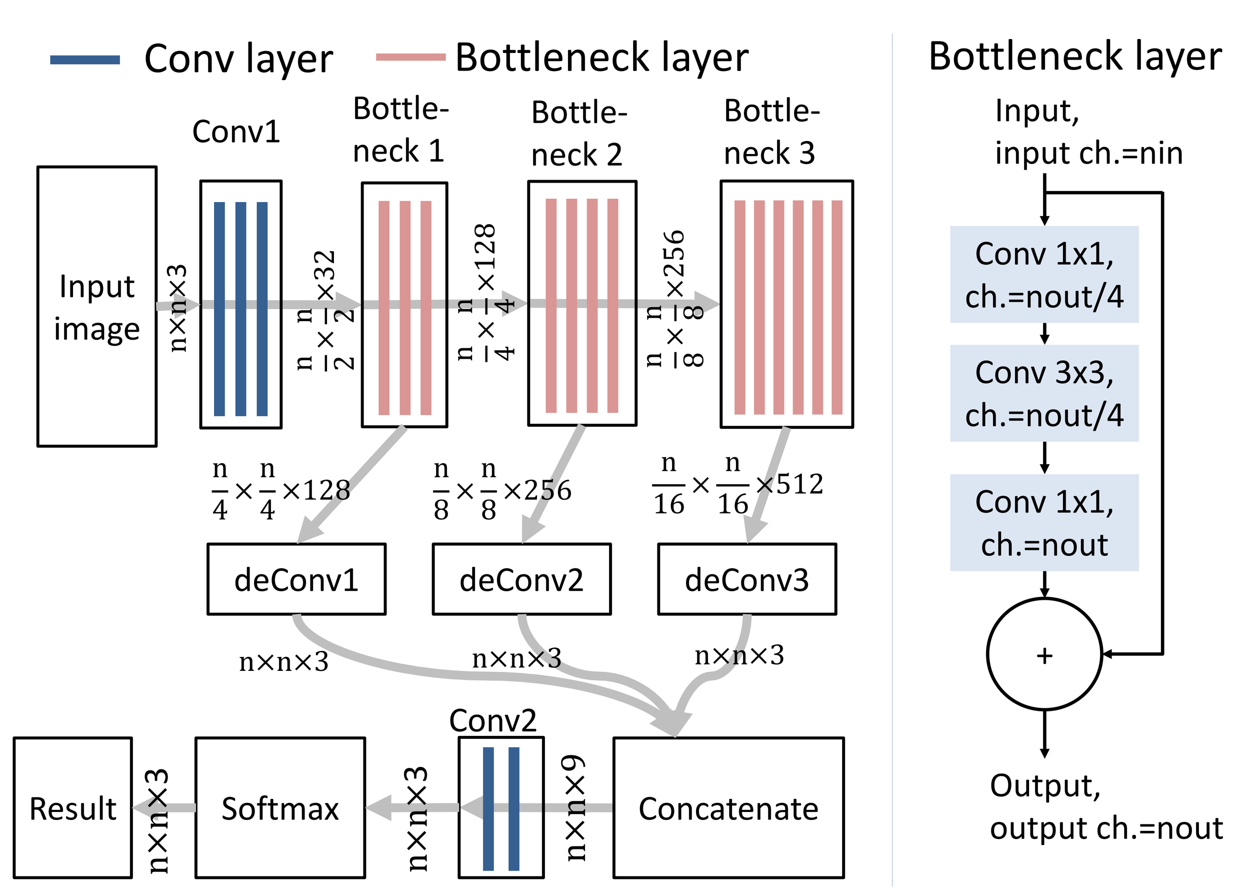

Fig. 6 (Left) Detailed structure of the FCN used in step three. Blue lines are convolution layers, while red lines are bottleneck layers. (Right) Detailed structure of one bottleneck layer. Batch normalization was applied after each convolution layer.

RESULTS

60 images were used in training, and 16 images were used in testing. The error of locating frameworks (absolute distance between the true position and the estimated position) using different image cropping methods were compared in Fig 7.

- Locating framework with Method 1 achieved the lowest mean-error, while locating framework with Method 2 achieved the lowest max-error.
- Although Method 3 has the highest input image size and resolution, it obtained the highest max and mean error for Lambda and Bregma points.

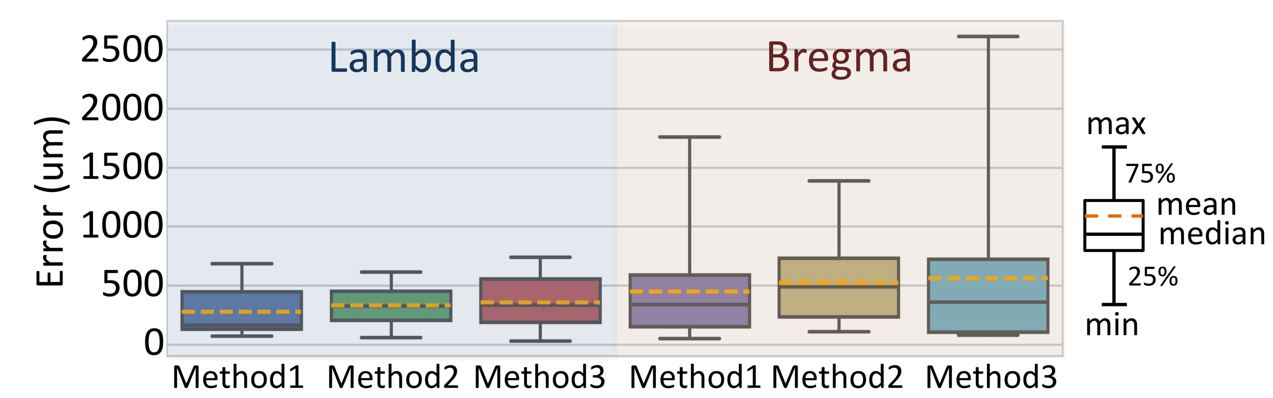

Fig. 7 Locating errors of the Bregma/Lambda locating framework with different image cropping methods.

Fig. 8 plots the estimated Lambda/Bregma positions from locating framework using cropping Method 2.

- For both Lambda and Bregma, the mean locating errors were less than 500um.
- Bregma points have locating errors majorly from "head->tail" direction, while Lambda points have more balanced errors from two directions. This is caused by the underlying texture of the skull.

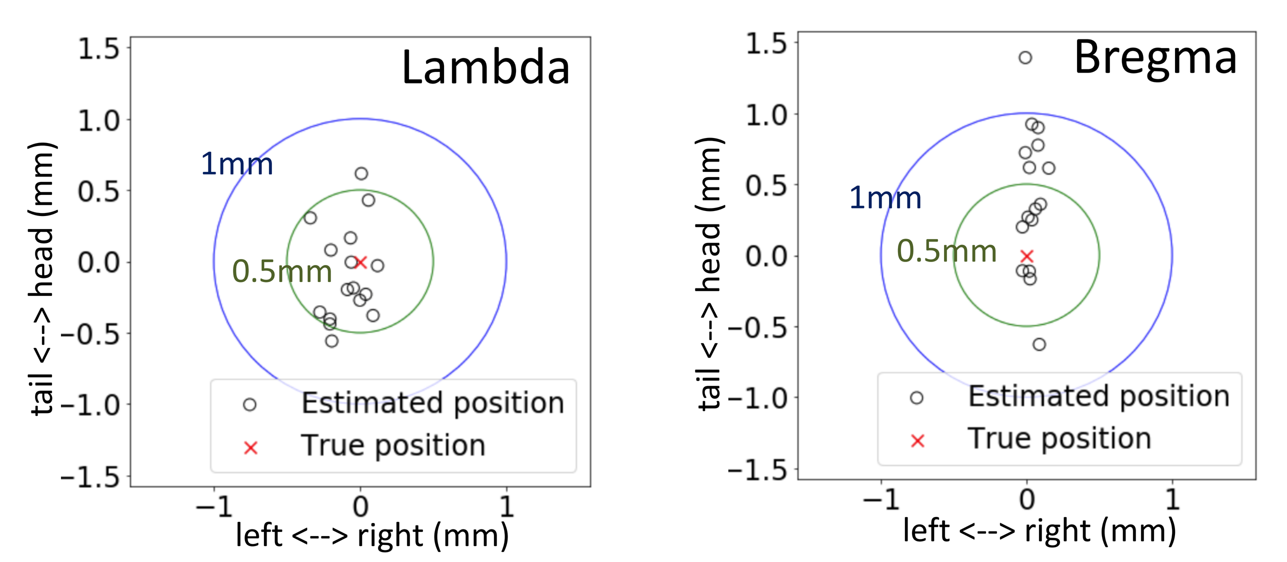

Fig. 8 Estimated positions for Lambda and Bregma from locating framework with image cropping Method 2. Red cross denotes the ground truth position, while black circles illustrate estimated locations for Bregma/Lambda in each of the 16 tested images.

Conclusions

- The proposed framework located Bregma and Lambda with mean error less than 500um.
- For the same network structure, a higher resolution image may not lead to a lower locating error. The current framework works best with Method 2.
- In the future, more images will be collected to improve network performance, and other network structures will be explored such as multi-task learn.

REFERENCES

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