Deep Learning in Processing Medical Images and Calculating the Orbit Volume

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Abstract

A software tool for calculating the volume of a soft-tissue eye orbit using the deep learning of neural network Mask R-CNN has been developed and tested. The result of the development will be in demand when evaluating the results of surgical intervention for the reconstruction of the thin bones of the orbit. It was established that the inaccuracy in constructing the contour of a soft-tissue orbit is 4–8%.

Keywords

Orbit · Orbit volume · Deep learning · Neural network · Biomedical images

1 Introduction

One of the criteria for evaluating the results of surgery to eliminate post-traumatic defects of the orbital bones is the calculation of the volume of the orbit before and after surgery. Currently, the estimation of the orbit volume is carried out using software tools to visualize the results of X-ray computer tomography in three projections and methods of layer-by-layer calculation of the orbit volume based on the spots set by the surgeon [1–3]. Along with the assessment of the orbit volume, there is an assessment of the tendency for changes in the volume of various types of tissue in the orbit [4].

At the same time, the analysis of the images obtained in the MSCT [5–7] in the DICOM [8] format and the three-dimensional reconstruction of the skull allows the surgeon to more reliably estimate the anatomical features of the individual patient, localization, boundaries and prevalence of the pathological process, and plan the scope of the surgery [9, 10].

The purpose of the project was the development of software tool for calculating the orbit volumes by using neural network machine learning technologies.

2 Experimental Technique

2.1 Initial Data

The results of microspiral computer tomography of 70 patients with fractures of orbit bones of varying severity were used as initial data for neural network learning. For each patient, a set of images in the DICOM format, obtained using the results of the Siemens Emotion 6 Microspiral Computer Tomography Scanner (Germany), was analyzed.

The preparation of images for neural network learning was carried out by layering these images. Before the marking process, DICOM images were converted to RGB images. The VGG Image Annotato application was used as a data marking tool. It is an application for manual annotation of images with the ability to perform multiple marking. The results of the marking are files in csv and json format, which store the information about the coordinates of the points bounding the polygon (the result of the marking of the orbit) in relation to the file name. Figure 1 shows an example of the marking of the initial files.

Initial data was divided into training and test in a percentage of 80 and 20%, respectively. Test initial data was used to test the operation of the neural network after learning. In addition, the test initial data was used as a control experiment to compare the results of the calculation of the volume of the orbit marked by the neural network with the volume of the orbit marked by hand.

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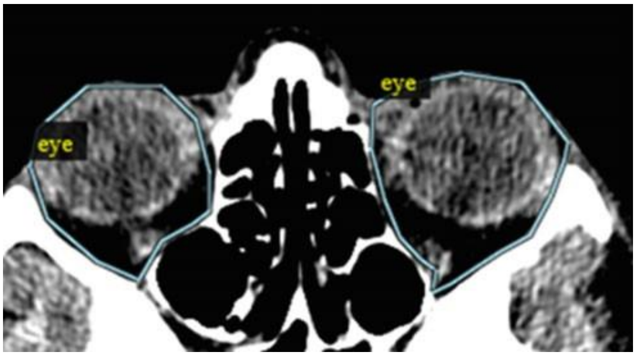

Fig. 1 The result of marking the initial data in one layer

2.2 Neural Network Learning

The task was solved by means of the Python programming language using the Anaconda platform. Tensorflow and Keras were used as the main frameworks for working with neural networks. A ready-made neural network architecture Mask R-CNN was used [5]. The neural network learning was started using the initial COCO weights [6] to ensure a faster learning process. The neural network learning had the following parameters: learning epoch—100, learning rate—0.001, regularization—0.0001, minimum probability at detecting—0.95.

2.3 Software Algorithm

The developed software works in two modes: the learning mode of the neural networks and the search mode for the contours of the orbits and the calculation of their volumes.

The algorithm of the software tool in the search mode for the contours of the orbits and calculation of their volumes consists of the following three procedures: (1) recognition of the contours of the orbit by the neural network by the input images in the DICOM format; (2) checking the correctness of the markings of the right and left orbits, correcting the results of the marking; (3) calculation of the volumes of the orbits and output of the results through the user interface.

The development of an additional procedure for unambiguous identification of the right and left orbits was required due to the fact that as a result of the neural network in some layers, the right orbit and left orbit were noted with an error: left as right, and right as left. Figure 2 shows the flowchart of the algorithm for correcting the recognition results of the orbit contours by the neural network.

In order to calculate the volume of orbits the following formula was used:

$$V = N \times a^2 \times h \quad (1)$$

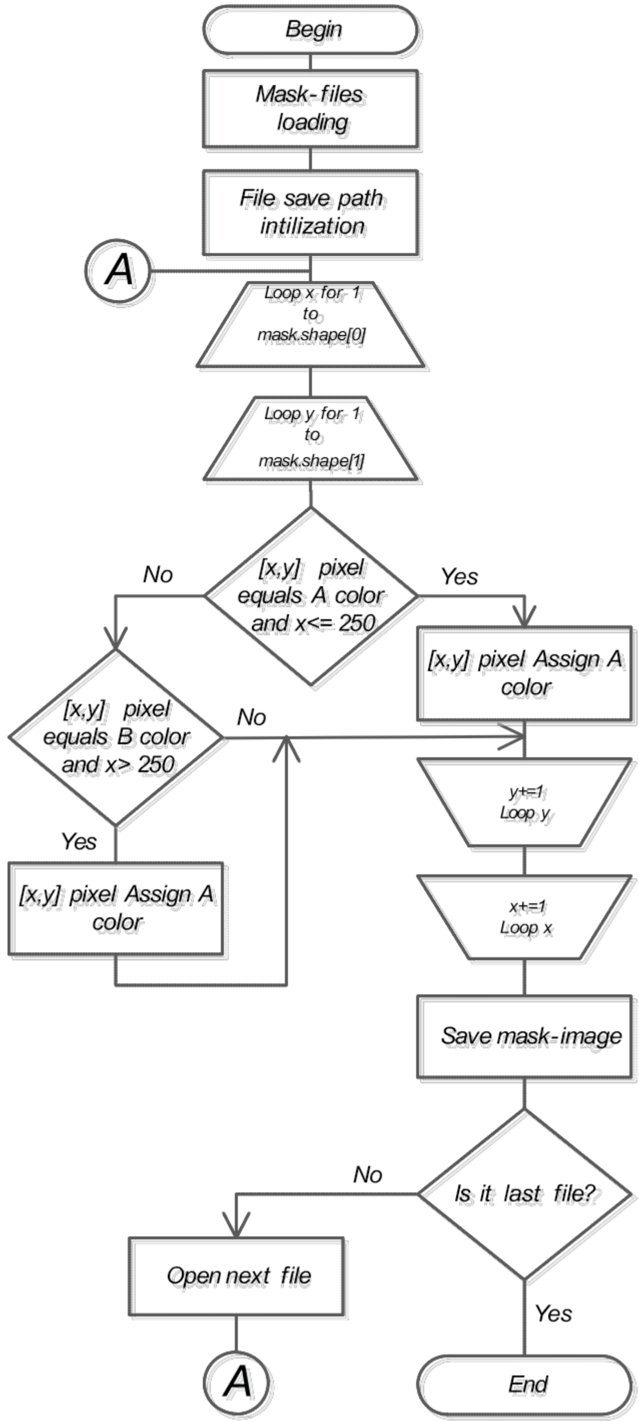

Fig. 2 Flowchart of the algorithm for correcting the results of the search for the orbit contours

where N is the number of pixels marked as part of the orbit; a is the pixel side length, mm; h is the distance between the layers, mm.

The pixel side length a and the distance between the layers h depend on the technical characteristics and resolving power of the microspiral computer tomography apparatus. In our case, the resolving power of the original DICOM files is 512×512 pixels and a = 0.455 mm, and the distance between the layers h = 0.625 mm.

The procedures implemented by means of the Python programming language were tested on 14 sets of DICOM files in order to estimate the marking error by the neural network of orbits.

3 Results and Discussion

As a result of neural network learning, a matrix of weights was obtained for each layer of the neural network on the basis of which the orbits were marked in the test data sets.

The typical Grid of ground truth objects and their predictions obtained as a result of the processing of the biomedical image layer are shown in Fig. 3.

After processing the images of the test data sets using the trained neural network and the procedure for correcting the search results, separate data sets were obtained—files with orbit contours. Figure 4 shows the result of the overlay of the orbit contours constructed by the neural network on the original image of the layer received by the software tool.

Further, based on the sets of files with the orbit contours, the volume of the right and left orbits was calculated using the formula (1).

Comparison of the orbits calculated by the results of the neural network marking with the volumes of the orbits calculated by the results of manual marking showed that the difference is 4–8%. This indicates the high accuracy of the marking of the orbits by the neural network. The proposed software tool is useful for automating the process of calculating the volume of orbits at the stage of preparation for the operation and in evaluating the results of the operation to replace the thin bones of the orbit.

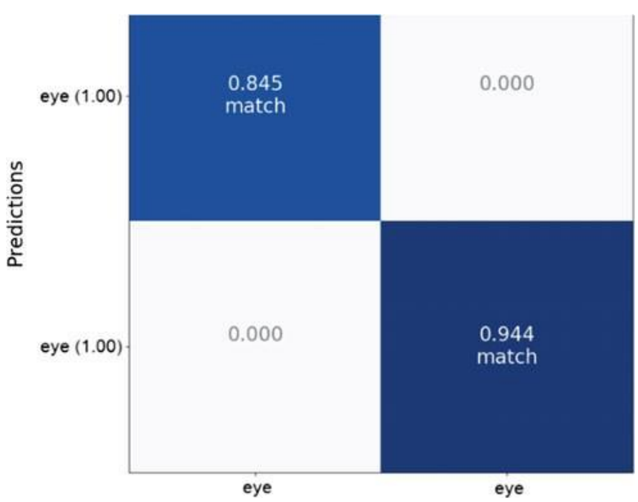

Fig. 3 Grid of ground truth objects and their predictions

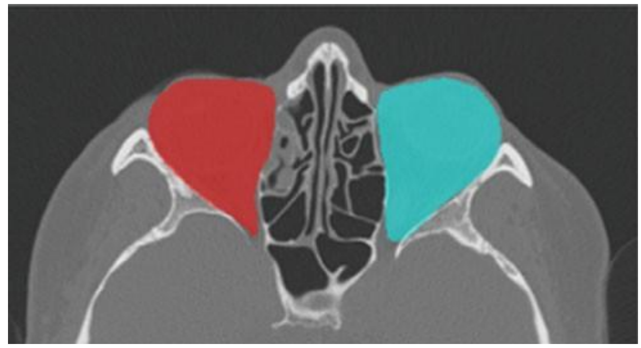
Fig. 4 The result of the search of the orbit by the neural network after learning

4 Conclusions

It has been established that the difference in calculations of the volume of orbits based on biomedical images (computer tomography results) using a neural network is 4–8%.

A software tool has been developed and tested to reduce the time spent on preparing for surgery to replace the thin bones of the orbit by 30–40 min.

Conflict of Interest The authors declare that they have no conflict of interest.

References

1. Levchenko, O.V., Krylov, V.V., Davydov, D.V., Lezhnev, D.A., Mikhayliukov, V.M., Sharifullin, F.A., Kostenko, D.I.: The computer tomography for estimation of surgical reconstruction efficacy for treatment of posttraumatic defects and orbit deformations. Russ. J. Neurosurg. 1, 29–33 (2014)
2. Levchenko, O.V., Mikhailiukov, V.M., Davydov, D.V.: Frameless navigation system for surgical treatment of posttraumatic defects and cranioorbital deformations. Russ. J. Neurosurg. 3, 9–14 (2013)
3. Davydov, D.V., Lezhnev, D.A., Kostenko, D.I.: Diagnostic MSCT and planning for surgical treatment for patients with orbital-wall injuries and post-traumatic deformities. Doctor.ru. Gastroenterol. 1 (118), 116–120 (2016)
4. IFMBE at https://studylib.ru/doc/2399666/v.a.-stuchilov-%E2%80%A2-a.a.-nikitin—moskovskij-oblastnoj-nauchno
5. Masalitina, N.N., Kurochka, K.S.: The automated classificatory of computer tomography results for lumbar spine geometric modeling. Doklady BGUIR 3, 12–19 (2017)
6. Patent 2000125015/14 RF A61B 17/80, A61B 17/56, A61F 2/28. Rybalchenkov's plate for reconstructing damaged bone structures of cheekbone, eye-socket and upper jaw complex and the way of reconstructing damaged bone structures of cheekbone, eye-socket and upper jaw complex with this plate. Rybalchenko, G.N.: Closed joint stock company "KONMET Incorporated". Rybalchenko, G. N.: Application № 2202302, 04 Oct 2000; Published 20 Apr 2003

7. Patent 2000116451/14 RF A61 F2/28. Method manufacturing an individual precision implant for compensation of complex subtotal polyostotic eye-socket defect. Shalumov, A., S.Z.; Shalumov, A., S.Z.: Application № 2164392, 27 May 2000; Published 27 Mar 2001
8. IFMBE at https://www.dicomstandard.org/current/
9. IFMBE at https://arxiv.org/pdf/1803.01534
10. IFMBE at https://github.com/matterport/Mask_RCNN/blob/master/samples/coco/inspect_weights.ipynb