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Landmark Localization On Color Coded Diffusion Anisotropy Images Using Convolutional Neural Networks

Ahmet Emin Yetkin[1], Andaç Hamamcı[1]

[1]Yeditepe University, Istanbul, Turkey

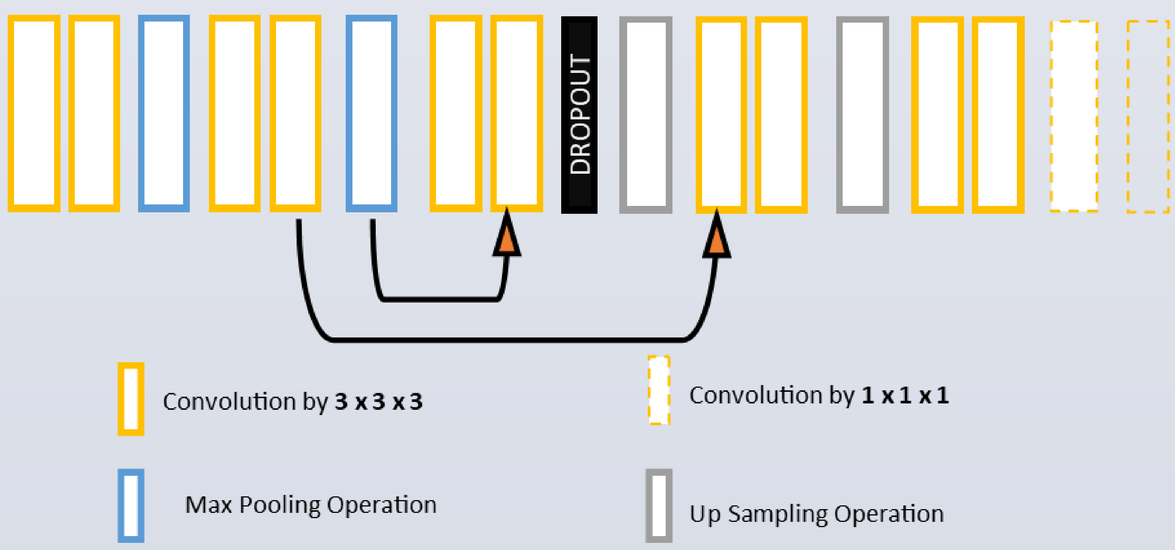
INTRODUCTION

Locating specific landmarks on brain images is one of the stages in defining the target in functional surgery and in estimating point wise correspondence in image registration [1, 2]. Diffusion tensor images are successfully implemented as the image term in deformable registration framework [3]. Those methods seek for a solution in local scale for the correspondence of the tissue microstructure with high degree of regularization. On the other hand, in [1], a method based on white matter fiber connection patterns derived from diffusion tensor imaging data is proposed to predict cortical landmarks, which are named as DICCCOLs, in a new single brain.

Convolutional neural networks (CNNs) have been outperformed earlier methods for two decades [4]. Nowadays, various types of CNNs have been proposed that are able to interpret so much complex problems. Landmark localization, finding exact location of structures in an image is a first stage of many complex computer vision problems such as objective of this study that a CNN based landmark detector is employed to locate specific landmarks at given MNI coordinates, on an individual's brain.

METHODS

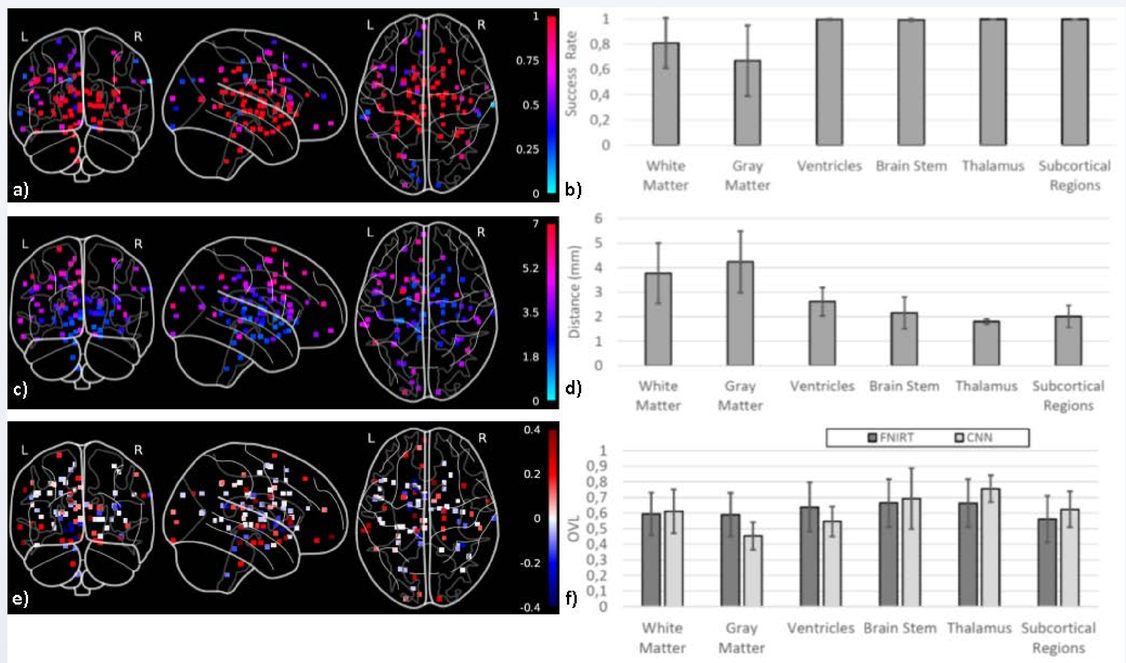
Pre-processed diffusion MR data of 400 randomly chosen subjects, which are available under the Human Connectome Project (HCP), are used in CNN training [5]. 90 landmarks are randomly selected in multiple brain regions using the Harvard-Oxford Subcortical Atlas in MNI coordinates Landmarks, de ned in MNI coordinates, are transferred to the subject's brain by using the deformation field, which is estimated on T1-weighted MR images by FNIRT tool of FSL [6]. For each landmark of each subject, a heat map is generated as a 3 dimensional Gaussian function centered at the landmark location. Patches are cropped from acquired color FA maps and used as input of CNN. The location of patch centers are randomly drawn from a uniform distribution on the brain mask. CNN is trained jointly for each of the 90 landmark points. 3x3x3 convolution kernels are used. After consecutive pooling and convolution operations, when the number of parameters becomes sufficiently small, instead of going under fully connected neurons for regressing coordinates of the desired landmark, network starts to increase the size of tensor by employing up sample layers. Last two convolution operations with 1x1x1 kernel size are applied to generate the heat map [7,8].



Layer structure of the CNN model.

RESULTS

Color FA maps of 50 randomly selected HCP subjects that are not included in training dataset, are used in evaluation studies. The final map is obtained by summing the output heat maps of the network for each patch and the location of the maximum is labelled as the landmark. To evaluate the performance of the proposed landmark detector, results are compared to locations that were marked by using FNIRT tool of FSL. 3 metrics are de ned : Success Rate: If the Euclidean distance of CNN prediction to FNIRT marked point is less than 1.25 cm, the prediction is considered as success, otherwise failure. Distance: The average of Euclidean distances of FNIRT and CNN proposed landmark positions on subjects, which satisfy success criterion, is calculated in milimeter unit. Accuracy: In order to evaluate the accuracy, overlap of eigenvector-eigenvalue pairs (OVL) measure, which compares the similarity of two tensor fields, is used [9].



Brain Region	Success Rate	Distance (mm)	FNIRT OVL	CNN OVL
White Matter	0.814±0.208	3.01±0.98	0.59±0.14	**0.61**±0.14
Gray Matter	0.667±0.283	3.37±1.00	**0.58**±0.13	0.45±0.08
Ventricles	0.998±0.006	2.09±0.46	**0.63**±0.16	0.54±0.09
Brain Stem	0.995±0.008	1.72±0.51	0.66±0.15	**0.69**±0.19
Thalamus	1.000±0.000	1.44±0.08	0.66±0.15	**0.75**±0.08
Subcortical	1.000±0.000	1.66±0.36	0.56±0.15	**0.62**±0.11
OVERALL	0.826±0.240	2.72±1.09	**0.60**±0.14	0.56±0.14

(g)

Mappings on glass brain template of success rate (a), distance (c), OVL scores (e), their regional averages (b,d,f), Average and standard deviations of the evaluation results for regions (g)

CONCLUSIONS

Landmarks located at the inner regions of the brain could be detected with higher success rate. Despite the possibility that this is because inner regions have richer characteristics, landmarks on ventricles, which are observed homogenous on color coded FA maps, are also located with high success rate. Although, the CNN training is performed by using the FNIRT labelled landmarks, the performance of CNN is higher at some regions. Therefore, the CNN does not learn the FNIRT labelling process but the underlying diffusion pattern.

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