Generation of head models for brain stimulation using deep convolution networks

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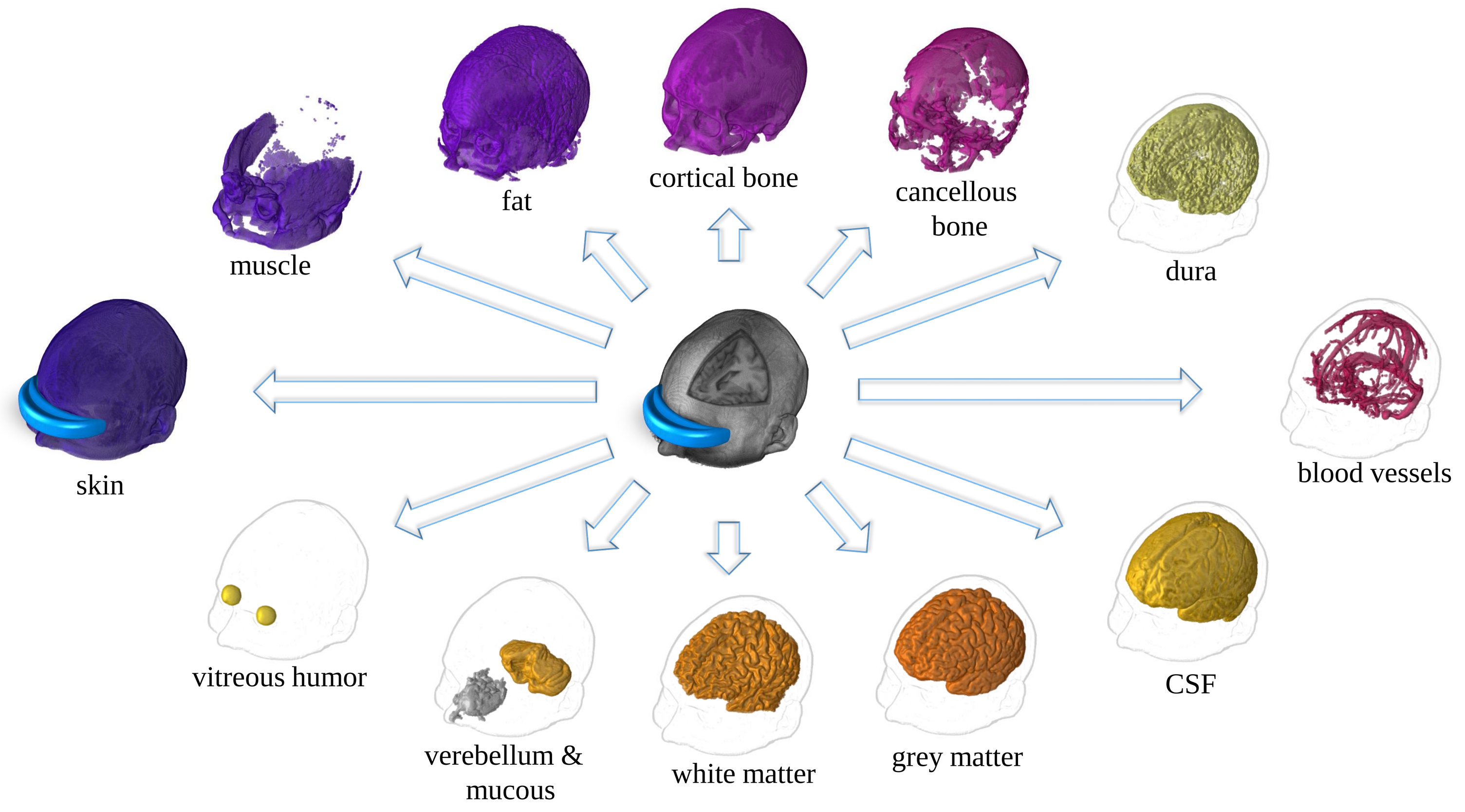
Introduction

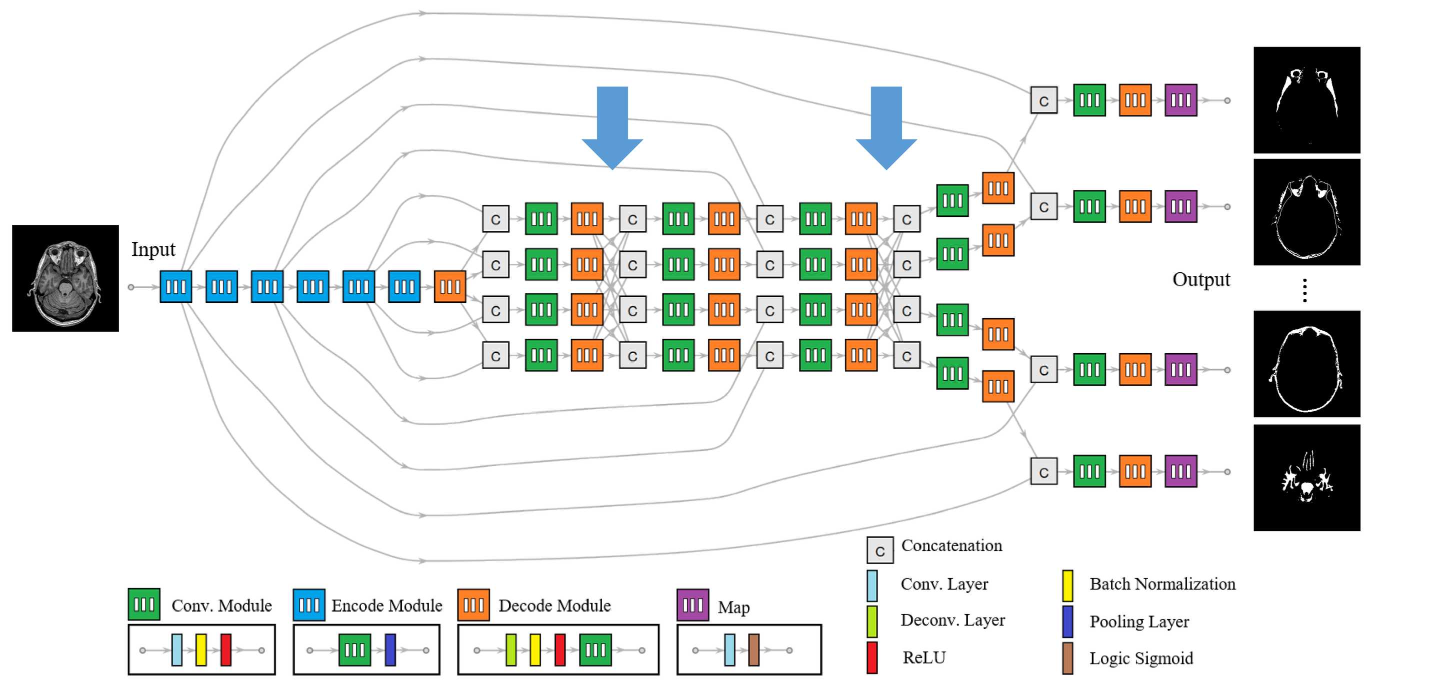
- Human head models are generated from anatomical images and used to generate volume conductor for brain stimulation applications.
- Fast generation of personalized head models are needed for stimulation planning and other clinical use.
- This task is challenging as it requires a segmentation of all head tissues (many appears in low-contrast in MRI).

Contribution

- Deep convolutional neural network (CNN) architecture is proposed to segment all head tissues using T1-w MRI.
- The proposed architecture has single encoder track and multi-decoders with interconnections.
- Results indicate that head models generated using the proposed method are of strong matching brain stimulation results compared with those generated manually.



Head model construction



#	Layer	Feature Size
	Input	256×256
1.	Enc_1	$8\times128\times128$
2.	Enc_2	$16\times64\times64$
3.	Enc_3	$32\times32\times32$
4.	Enc_4	$64\times16\times16$
5.	Enc_5	$128\times8\times8$
6.	Enc_6	$256\times4\times4$
7.	Dec_1	$128\times8\times8$
8.	$Con_{1,n}$	$2\times128\times8\times8$
9.	$Cnv_{1,n}$	$128\times8\times8$
10.	$Dec_{2,n}$	$64\times16\times16$
11.	$Con_{2,n}$	$N\times64\times16\times16$
12.	$Cnv_{2,n}$	$64\times16\times16$
13.	$Dec_{3,n}$	$32\times32\times32$
14.	$Con_{3,n}$	$2\times32\times32\times32$
15.	$Cnv_{3,n}$	$32\times32\times32$
16.	$Dec_{4,n}$	$16\times64\times64$
17.	$Con_{4,n}$	$N\times16\times64\times64$
18.	$Cnv_{4,n}$	$16\times64\times64$
19.	$Dec_{5,n}$	$8\times128\times128$
20.	$Con_{5,n}$	$2\times8\times128\times128$
21.	$Cnv_{5,n}$	$8\times128\times128$
22.	$Dec_{6,n}$	$4\times256\times256$
23.	Map_n	256×256
	$Output_n$	256×256

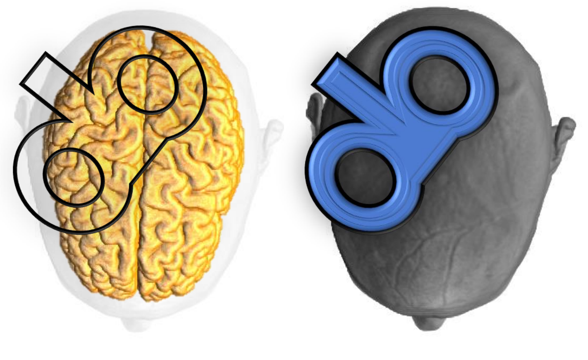
Proposed network architecture with $N=4$.

Network architecture

- 23 layer network with single input and N outputs.
- Individual decoders provide more robust design to avoid network confusion when segmentation labels is large.
- Interconnections provide feature exchange between different decoders. We have used two interconnections labeled by the blue arrows above.
- Segmentation is decides with high vote label and training is conducted with different slicing direction (axial, sagittal, and coronal).

Transcranial Magnetic Stimulation (TMS)

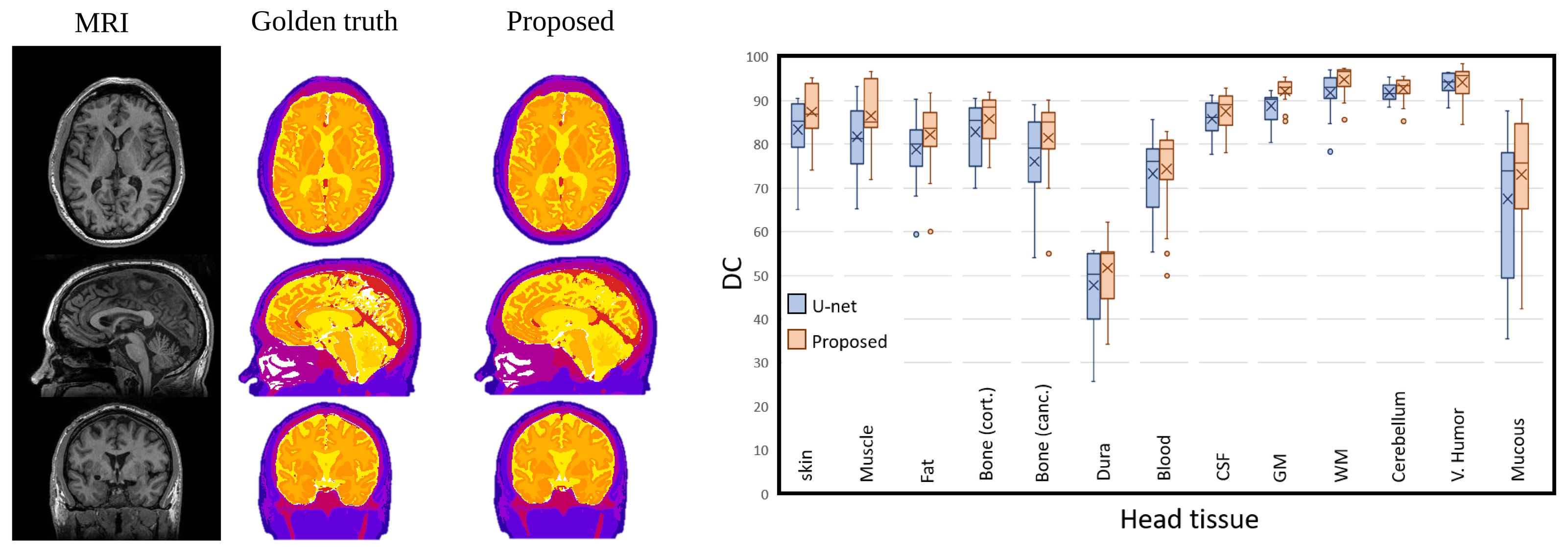
- Figure-eight TMS coil is located above hand motor area.
- Isotropic tissue conductivity is computed using Cole-Cole model for 10 kHz.



TMS coil position

Results

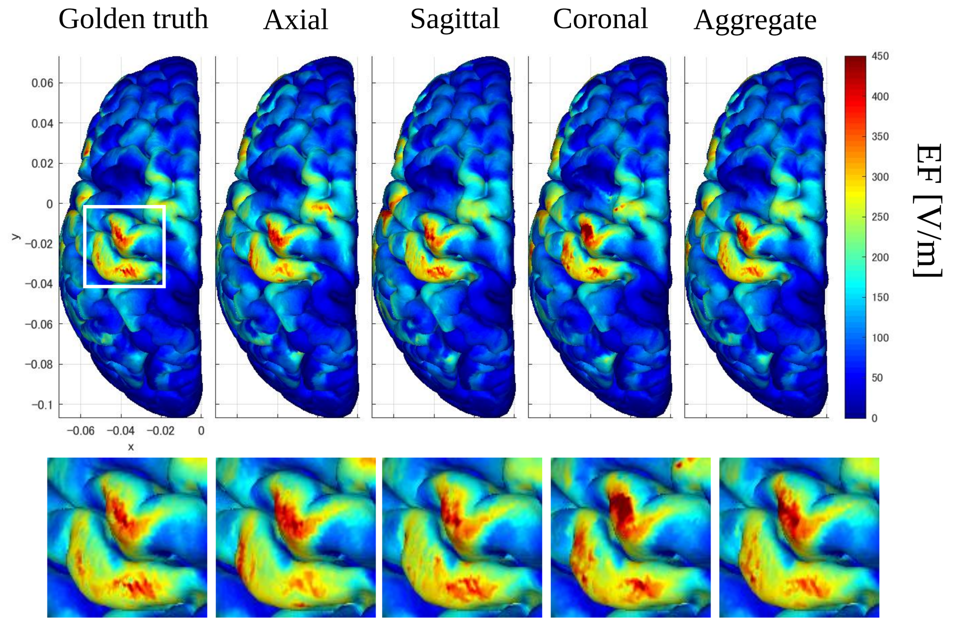
- Leave-one-out cross-validation of 18 subjects and 13 tissues.
- Training to minimize cross entropy cost function using ADAM algorithm for 10 epochs and batch size =2.
- High performance is achieved in brain tissues (e.g. GM, WM, and cerebellum) compared to non-brain tissues (e.g. dura, mucous, and blood vessels).
- Better dice coefficient can be achieved compared with conventional U-net architecture.



Segmentation results and DC comparison with U-net

Conclusion

- High matching in both segmentation and induced electric field is observed between models generated using proposed method and golden truth.



TMS induced electric field

More details are in our recent publication:

Rashed *et al.*, NeuroImage 202,116132, 2019