A Comparative Study of Deep Learning Based Image Registration Techniques

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Synopsis

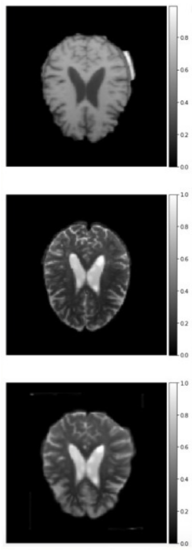
In recent years, deep learning algorithms have been used extensively in tackling medical image registration issues. As we investigate state-of-the-art methods for this problem, we came to realize that there is still scope for building better performant systems. In view of doing so, we have initially performed a survey and experimented with the most recent efforts in this field. We mostly kept our implementations very close to the guidelines provided by the authors. While doing so, we have basically established our assumption that we can work to develop faster, better, efficient systems that can be used in real-time.

Summary of main findings

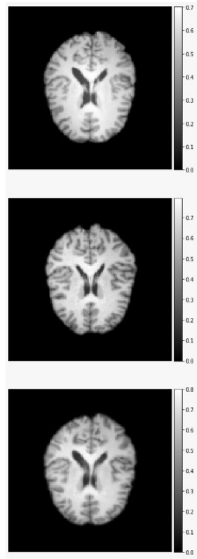
Comparison of existing algorithms provides guideline for a more efficient, better performant system.

Introduction

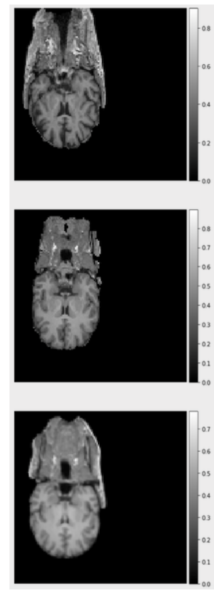
The impressive performance of deep learning algorithms has inspired many to implement them in solving a multitude of real life scenarios like medical image registration, but yet, not all of these algorithms are performing as we would hope for. In this research, we tried to come up with a novel approach to solve this crucial step for automating medical diagnosis and clinical procedures. In achieving this feat, we have initially performed an analysis on some of the established and proposed methods that we shall consider as our baselines. In this abstract, we are presenting our findings based on our experiments with those thus far.



(a) intermodal, affinely registered images, 1000 epochs



(b) intramodal affinely registered images, 1000 epochs



(c) intramodal, raw images, 1000 epochs

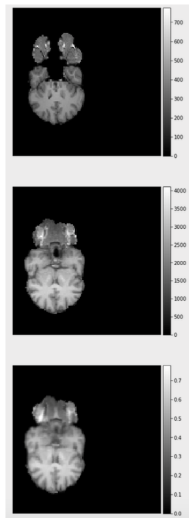
Figure 1: Result from experiments with VoxelMorph

Methods

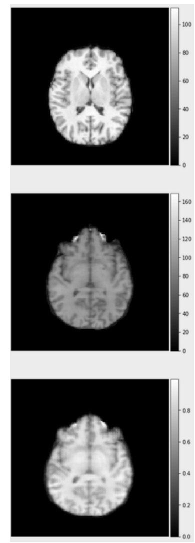
For the purpose of comparison with our method, we have selected three algorithms: VoxelMorph[1], ADMIR[3], ICNet[5]. VoxelMorph, as we know it, takes a pair of affinely aligned moving and fixed images[1] and calculates the deformation field by learning a set of parameters defined using a convolution neural network. ADMIR took this approach a step further and created an end-to-end pipeline[3] where, as part of the pipeline, at first the raw images are transformed affinely, then it gets registered deformably. On the other hand, ICNet introduced two explicit constraints on the model namely inverse-consistent and anti-folding constraint[5], which helps to guide the model to generate more realistic deformations in comparison to those without these constraints, since DL methods are prone to generate unrealistic deformations and a strong regularizer is always required while defining the deformation function.

Results

For performing these experiments, we relied on IXI[2] dataset that is publicly available. We used AntsPy and FSL tools to preprocess our images. Here, by preprocessing we are mainly referring to skull-stripping, and affine registration, both of which were done using FSL, and resampling which was done using



(a) intramodal, raw images, 100 epochs



(b) intramodal, affine registered images - 100 epochs

Figure 2: Result from experiments with ADMIR

AntsPy library. Thus we produced the ground truth for training our algorithm. We tried to keep ourselves constrained to the implementation suggested by the authors, but in some places we have done some variations and/or experiments of our own, just to verify if we could get any better results by modifying or fine-tuning the models.

Discussion

VoxelMorph[1] model was trained on both raw and affinely registered, pre-processed images. The dataset consisted of 200 images and was trained for 1000 epochs. Here, we observed that VoxelMorph intramodal model couldn't morph as expected if the fixed and moving images were not affinely aligned and preprocessed. There were some missing information and slight blurring in warped images. On the other hand, VoxelMorph intramodal model on preprocessed images provided comparable results to that mentioned in the paper. We saw the brain folds of moving images deform as per fixed image and with more training, the blurring was reduced. VoxelMorph intermodal model was trained on preprocessed and affine registered images with similarity loss as mutual information. We observed that more bins led to better registration. Due to our limited computation power, we could only use 10 bins for mutual information loss and better registration results were seen here, albeit with slight blurring. Hence we believe that with more compute and bins, registration should work

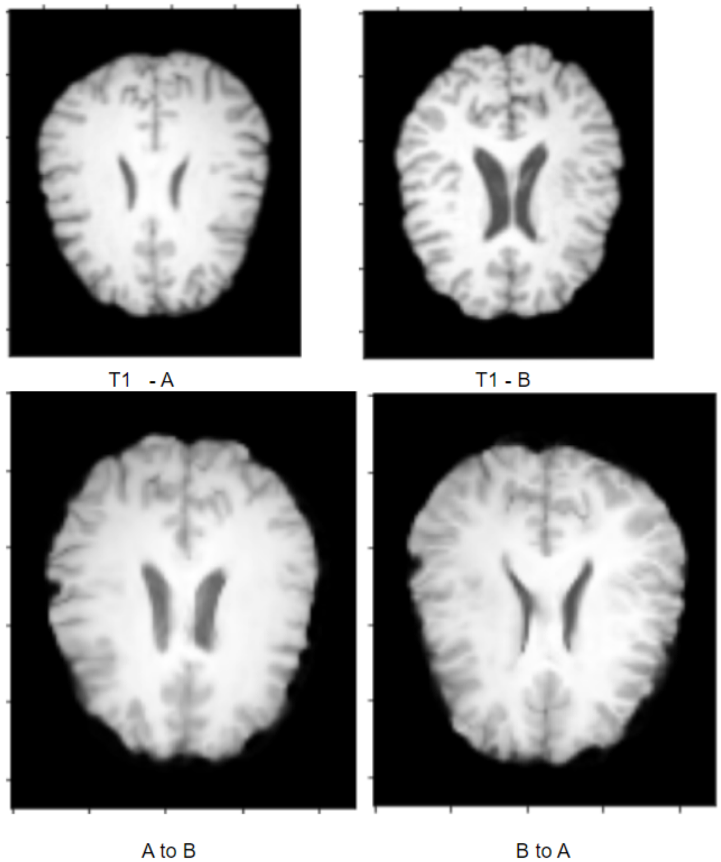


Figure 3: Result from experiments ICNet with 100 epochs

much better.

As for ADMIR[3], we were unable to stabilize the affine network, the initial stage of the pipeline, during training. The affine parameters caused too much shearing, and only the deformable part worked. As the coarsely warped image sheared too much, the correlation loss went to maximum causing too much load for the deformable network to correct it back.

For ICNet[5], we observed similar results. As we increased the number of epochs and the dataset size for training, we noticed that the registration process was performing better. This only works for pre-affinely registered images. We can see from the figure that moving image A is trying to replicate fixed image B (result in A to B) for some parts of the brain. But, unfortunately, results are not as expected as we had hoped, mostly because complete warping did not take place and there was blurring in the result. But, if we consider the outcome of the ICNet paper, we realize that this result of ours can perform a lot better.

Algorithm	IntraModal		InterModal	
	Ants	FSL	Ants	FSL
VoxelMorph	0.9607	0.9277	0.9151	0.8894
ADMIR	0.9351	0.9591	-	-
ICNet	0.9549	0.9343	0.9114	0.8962

Table 1: SSIM[4] similarity indices for our experiments

Conclusion

To conclude, we have seen that there is still work to do to deliver a remarkable solution that would alleviate the burdens of clinicians and would serve human-kind with a more accurate diagnosis, and we plan to do so in our implementation.

References

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