MATHEMATICAL PHYSICS

Conference materials
UDC 004.032.26
DOI: https://doi.org/10.18721/JPM.173.168

Improving compliance of brain MRI studies with the atlas using a modified TransMorph neural network

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Abstract. The work carried out a study on modifying the architecture of the TransMorph neural network by integrating an input data preprocessing unit. The goal was to achieve better similarity scores between studies in the dataset and the reference atlas. The data was assessed based on the structure similarity metric. The results suggest that the use of a Sobel filter can lead to improvement.

Keywords: DIR, TransMorph, brain segmentation, MRI, neural network, AI in medicine

Citation: Nefediev N.A., Staroverov N.E., Davydov R.V., Improving compliance of brain MRI studies with the atlas using a modified TransMorph neural network, St. Petersburg State Polytechnical University Journal. Physics and Mathematics. 17 (3.1) (2024) 335–339. DOI: https://doi.org/10.18721/JPM.173.168

Материалы конференции
УДК 004.032.26
DOI: https://doi.org/10.18721/JPM.173.168

Улучшение соответствия МРТ исследований головного мозга атласу при помощи модифицированной нейронной сети TransMorph

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Аннотация. В работе проведено исследование по модифицированию архитектуры нейронной сети TransMorph путем встраивания блока предобработки входных данных. Целью было достижение лучших показателей схожести между исследованиями из набора данных и эталонным атласом. Оценка данных проводилась на основе метрики structure similarity. Результаты позволяют сделать выводы, что применение фильтра собеля может привести к улучшению.

Ключевые слова: DIR, TransMorph, сегментация мозга, МРТ, нейронные сети, искусственный интеллект в медицине

Ссылка при цитировании: Нефедьев Н.А., Староверов Н.Е., Давыдов Р.В. Улучшение соответствия МРТ исследований головного мозга атласу при помощи модифицированной нейронной сети TransMorph // Научно-технические ведомости СПбГПУ. Физикоматематические науки. 2024. Т. 17. № 3.1. С. 335–339. DOI: https://doi.org/10.18721/JPM.173.168

Introduction

Deformable image registration (DIR) is an important task in the field of image processing. In general, DIR is the spatial correlation of objects in one image (displaced) to another image (fixed or reference). From a practical point of view, this task is one of the fundamental tasks in the field of medical image processing, especially where there are series of images (computer tomography like research).

When working with diagnostic radiology studies, especially with MRI and CT studies, a situation often arises when a specialist receives a deformed series of images. Deformations of CT and MRI studies often occur due to shifts in the patient's position relative to the positioning of the specialist or the urgency of the study, when it is not possible to perform the correct positioning. Such cases contribute to the fact that the output series contains rotations of the patient relative to the standard placement or unclear boundaries of internal structures due to random movements.

One solution to the problem of image deformation is the use of classical image registration algorithms. The principle of operation of such algorithms is to process two images, solve the problem that is the basis of the algorithm and, based on the solution found, change the target image relative to the reference one. The main advantage of solutions of this kind is that they work based on clear and easily interpreted rules, and, unlike neural networks, they do not require training. The main disadvantage of this approach is the high cost of calculations and, therefore, the speed of their operation. Despite the attempt to transfer calculations to the GPU, solving the DIR problem using most classical algorithms can take minutes or even more. When solving a problem for multi-slice CT or MRI studies, this together can lead to significant processing time for the entire series. This significant drawback greatly complicates the application of solutions based on classical algorithms in real practice.

An alternative to classical algorithms are solutions created on the basis of neural networks. The field of medicine was no exception. In the context of interaction with MRI and CT series, advanced results are achieved using algorithms based on neural networks. The main problem in the use of neural network algorithms for analyzing research in medicine most often lies in the fact that training occurs on a set of studies with unclear semantics, and when processing a deformed study, various types of errors may occur.

To eliminate biases, the study uses image registration algorithms. Among neural network algorithms, two subtypes can be distinguished, namely neural networks that learn with and without a teacher. To train the first type of networks, a ground truth data set is required, which acts as a reference result of the processed research: at each stage, the option predicted by the network is compared with the ground truth and based on this comparison, the error is calculated, and a decision is made to direct the further training step. Often in this approach, a set of ground truths is created using classical algorithms. For unsupervised learning, only a rule is required by which the error metric will be calculated. During the learning process, the network itself will select the optimal rules for changing the image to minimize errors. Currently, algorithms based on unsupervised learning show state of the art results in solving the DIR problem. We explored the possibility of using a modified TransMorph architecture to improve brain MRI data [1].

Materials and methods

For solving the DIR problem, algorithms solve a typical energy optimization problem between two images:

$$E(I_m, I_f, \phi) = E_{sim}(I_m \circ \phi, I_f) + \lambda R(\phi), \tag{1}$$

where I_m и I_f is shifted and fixed image, ϕ is deformation field, which distorts the shifted image (i.e. $I_m \circ \phi$), $R(\phi)$ ensures the smoothness of the deformation field, λ is the regularization hyperparameter that determines the tradeoff between image similarity and deformation field regularity.

This equation reduces to solving the optimization problem:

$$\hat{\phi} = \arg\min_{\phi} E(I_m, I_f, \phi), \tag{2}$$

The DIR reference study was the brain atlas. The atlas also served to calculate the structural similarity index measure (SSIM) for the studies under consideration [2, 3]. SSIM is one of the methods for assessing the similarity of two images and displays the structural changes of one image relative to the reference:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}, \tag{3}$$

where μ_x and μ_y are mean x and mean y respectively, σ_x^2 and σ_y^2 are variance x and variance y respectively, σ_{xy} is the covariance between x and y. $c_1 = (k_1 L)^2$, $c_2 = (k_2 L)^2$ – two variables, in which L is the dynamic range of the pixel-values ($k_1 = 0.01$, $k_2 = 0.03$ by default).

When working with images, in addition to approaches based on the use of algorithms (classical or neural network), image filtering is often used. This approach is based on applying a filter kernel to an image to obtain a new one. Depending on the filter settings, the new image can have various properties, i.e. highlighting edges, suppressing noise, changing sharpness, as well as changing parameters such as brightness and contrast, as well as aligning their values. The processed image can be better perceived by a specialist (for example, in the medical field) or participate in a further pipeline. It is worth noting that there are a huge variety of filters for image processing that allow you to highlight target features in the input data. In our work, we used the Sobel filter, which allows us to find the boundaries of image objects, and the operating principle is based on calculating local changes in the pixel area.

In our work, we used the open dataset "Information eXtraction from Image" – IXI [4]. The dataset contains about 600 MRI studies performed in T1, T2, PD-weighted images. To carry out our work, we used T2 studies.

The first step was to study the structural correspondence of the existing studies in the dataset to the reference atlas. The SSIM metric was used to calculate structural fit. The next step was to align studies from the existing dataset against the atlas and recalculate the SSIM for the processed dataset and atlas. We used the TransMorph architecture, which is based on the idea of using Swin Transform as an encoder [5]. In Transmorph, SWIN Transform blocks have been configured, which adapts the self-attention mechanism for the DIR task and improves the usefulness of the method relative to conventional self-attention. An increase in the metric was obtained.

The next step was to modify the TransMorph network and apply its modified version to the dataset. To modify the architecture, the original architecture with trained weights was taken from the TransMorph authors' github repository. We have built into the architecture a convolutional layer for processing input data with parameters of 128×128×32, a customized convolution kernel according to the Sobel filter. The modified architecture is shown in Figure 1, the internal structure of two successive swin transformer blocks is shown in Figure 2.

In the modified network, the input data first passes through the convolutional layer, from where it is transferred to the original TransMorph part. The resulting displacement field is applied to the original input data. An example of data after the convolutional layer is given in the next section.

Results and Discussion

Figure 3 shows data from the dataset in the form of single slices before pre-processing by the convolutional layer (top row original) and after the convolutional layer (bottom row after filter).

The impact of the original and modified versions of TransMorph was assessed on 20 randomly selected studies from the IXI dataset. The evaluation was carried out using the SSIM metric, which was calculated at the research step. The results obtained are shown in Figure 4.

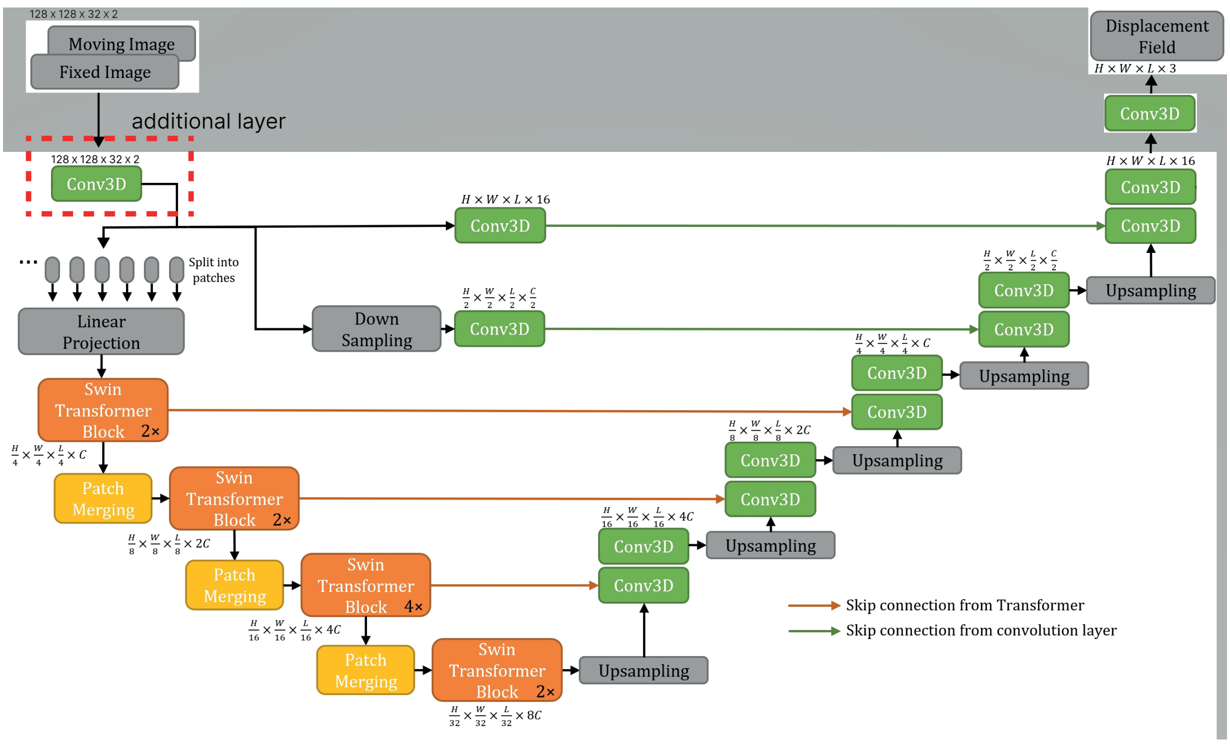

Fig. 1. Modified TransMorph architecture

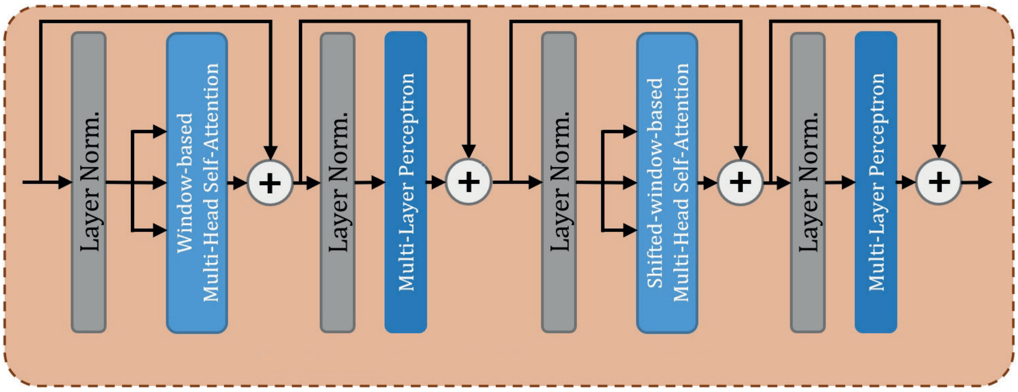

Fig. 2. Internal structure of two successive swin transformer blocks

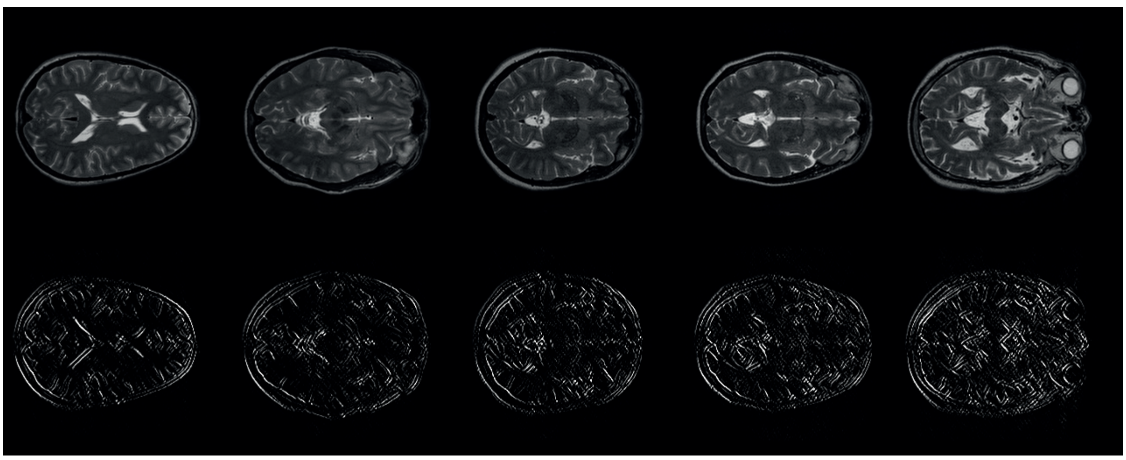

Fig. 3. A single slice of the series after additional layer

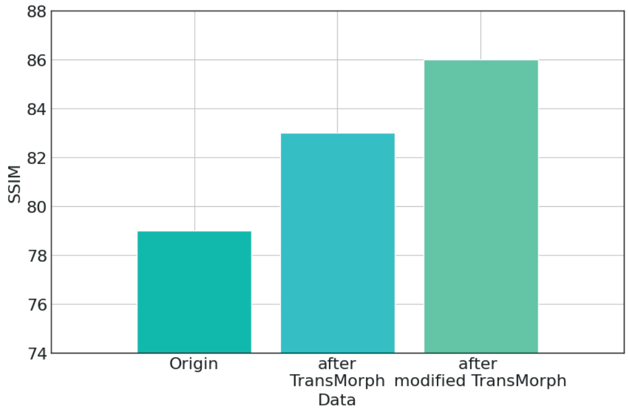

Fig. 4. SSIM metric value on original data and after applying TransMorph and modified version

Conclusion

The research work carried out shows the prospects for using data preprocessing for DIR. If positive results are obtained on a more variable dataset, the next step is to use the processed data to train segmentation networks and analyze MRI studies of the brain.

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Received 14.07.2024. Approved after reviewing 27.08.2024. Accepted 28.08.2024.