Retraction

Retraction: Unsupervised registration of intravascular ultrasound images combined with attention mechanism (J. Phys.: Conf. Ser. 1873 012030)

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This article has been retracted by IOP Publishing following an allegation and subsequent investigation regarding the author’s use of IVUS datasets. The datasets used are the property of IVUS-challenge 2011 organizers and were used without approval from the data owner and contravening the distribution policy of the dataset.

IOP Publishing have tried repeatedly to contact the authors of this article but have not received a response. IOP Publishing encourages the authors to contact us at researchintegrity@ioppublishing.org.

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Unsupervised registration of intravascular ultrasound images combined with attention mechanism

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Abstract. For intravascular ultrasound (IVUS) images, the registration technology is used to calculate coronary arteries displacement to analyze vascular elasticity. It not only provides evidence for the prevention and treatment of cardiovascular diseases, but also has important significance for guiding interventional surgery and monitoring the placement of surgical stents. Aiming at the high computational cost of current traditional registration methods and the insufficient accuracy of common deep learning registration methods for IVUS images, this paper proposes a fast unsupervised registration of IVUS images combined with an attention mechanism. The proposed method directly learns to estimate a displacement vector field (DVF) from a pair of input images of the training set. The spatial transform network (STN) uses the DVF to transform the moving image into the fixed image. Finally, the model is trained by minimizing a similarity metric loss function between the deformed moving image and the fixed image. Compared with the previous deep learning method, the registration performance improved after implementing the proposed method. The proposed method can accurately register the inner and outer membranes of IVUS images and provide a reliable basis for vascular elasticity analysis.

1. Introduction
The definition of medical image registration is that for two images in a set of image data sets, one moving image is mapped to another fixed image by looking for a spatial transformation, so that the two images correspond to each other. For IVUS images, registration technology can calculate the deformation displacement field of the blood vessel wall to analyze the elasticity of the blood vessel [1], and study the early detection of fragile plaques and the risk of plaque rupture, which is of great significance for guiding interventional surgery and monitoring the placement of surgical stents [2]. The research content of IVUS image registration is how to accurately find the displacement field of two IVUS images.

The basic idea of the traditional image registration method [3] is to first define the image similarity measure, and then use the iterative optimization method to search for the optimal parameters, which leads to the fact that its processing speed is equivalent slow and difficult to apply to real-time scenarios. To solve this problem, researchers applied deep learning in the field of image registration. Although these papers [4] show good registration results, most of which are supervised learning methods. In other words, they all need the ground truth deformation fields to support the experiment, but in fact they are difficult to obtain.

Several recent works have proposed deformable image methods based on unsupervised learning. Convolutional neural networks are designed to learn coarse-grained spatial transformations by optimizing...
image similarity measures \cite{5}. Similarly, recent work \cite{6} proposed a method that directly outputs fine-grained deformation fields. They use regularization techniques to obtain spatially smooth and physically reasonable transformations. Their registration accuracy is comparable to the most advanced image registration algorithms.

Most of these methods work on MRI brain images or chest CT images. Compared with these image registrations, IVUS image registration is more challenging due to its poor image contrast, narrow grayscale range, and strong texture self-similarity. In order to overcome the challenges of IVUS image registration, this paper proposes an unsupervised intravascular ultrasound image registration combined with an attention mechanism.

2. Methods

2.1. Improve loss function

The purpose of image registration is to find the spatial transformation \( \phi : I_M \rightarrow I_F \) between the image pair. The overall performance of the registration model is affected by the network structure and loss function. The loss function of the registration network has two parts, one is the image similarity loss measurement \( S(\cdot) \), and the other is the smooth regularization term \( D(\cdot) \).

\[
\text{Loss}(I_F, I_M, \phi) = S(I_F, I_M(\phi)) + D(\phi)
\]  

\( S(I_F, I_M(\phi)) \) represents the image similarity loss metric, and \( D(\phi) \) represents the smooth regularization term.

Given that IVUS images have similar image intensity distribution and local contrast, the image similarity loss metric in this paper uses mean-square error (MSE) and local cross-correlation (LCC) for comparison experiments.

\[
S(I_F, I_M(\phi)) = \text{MSE}(I_F, I_M(\phi))
\]  

\[
S(I_F, I_M(\phi)) = 1 - \text{LCC}(I_F, I_M(\phi))
\]

Where \( I_M(\phi) \) is \( I_M \) warped by \( \phi \).

The minimized image similarity measurement will make the registered image \( I_M(\phi) \) closer to the fixed image \( I_F \), but this will easily cause the deformation field \( \phi \) to be unsmooth and discontinuous. Therefore, it is necessary to add a constraint term to smooth the deformation field \( \phi \). Unlike many methods that only penalize the first derivative of \( \phi \), this paper adds a bending penalty \cite{7} to \( \phi \). This term penalizes the second derivative of the local transformation of \( \phi \).

\[
D(\phi) = w_1 R(\phi) + w_2 P(\phi)
\]

\( R(\phi) \) and \( P(\phi) \) represent different smoothing regularization terms. Among them, \( R(\phi) \) is the first-order penalty regular term, and \( P(\phi) \) is the bending energy penalty regular term. The \( w_1 \) and \( w_2 \) are regularization term coefficients, which are used to weigh the proportions of the two regularizations.

2.2. Network Architecture

The IVReg-Net network proposed in this paper is similar to U-net and VoxelMorph. The input of the network is a pair of image fixed image \( I_F \) and moving image \( I_M \), which are connected in pairs to form a 2-channel 2D image. After the network outputs \( DVF \), STN applies \( DVF \) to \( I_F \), and finally generates a deformed registration image \( I_M(\phi) \). The registration network is trained by calculating the loss function between \( I_M(\phi) \) and \( I_F \).
The IVReg-Net network is a multi-layer neural network. The encoder-decoder with three skip connections combines the attention gate mechanism\cite{8} to form the IVReg-Net network. The network encoder has 4 down-sampling processes, and each down-sampling process includes a convolutional layer with a convolution kernel size of $3 \times 3$ and a step size of 2 and a LeakyReLU activation function layer. The output feature map channels of these 4 convolutional layers are 16, 32, 32, 64, respectively. In the encoder, in order to retain more position information, stride convolution is used to replace the traditional pooling method.

The network decoder includes up-sampling process, convolution process, skip connection and attention gate mechanism. The first 6 layers of the decoder are alternate up-sampling process and convolution process. Each up-sampling process is an UpSampling layer, and the UpSampling layer restores the image dimension through transposed convolution operations. Before the convolution operation, the skip connection takes the down-sampled low-level features from the encoder and the high-level features from the decoder as input to the attention gate mechanism. The output of the attention gate and the up-sampling feature maps are merged by Concatenate, and the merged result is used as the input of the convolution process. The convolution process includes a convolution layer, the size of the convolution kernel is $3 \times 3$, the step size is 1, and the LeakyReLU activation function layer. The last 2 layers of the decoder are convolutional layers. The number of channels of the output feature map of these 8 layer decoder is 64, 64, 32, 32, 32, 32, 16, 2, respectively. The structure and depth of the IVReg-Net network are the results of many experiments.
In the IVReg-Net network, the attention gate mechanism calculates the gradient through the neural network, and obtains the attention weight $\alpha$ through forward propagation and backward feedback learning. The attention weight $\alpha$ is multiplied by the low-level feature map will cause the target area value in the feature map to become larger and the non-target area value to become smaller. Therefore, the network model can better pay attention to areas with large morphological differences during the training. The attention gate module uses only $1 \times 1$ convolutional layer, which means that introducing a small number of parameters can significantly improve the sensitivity and registration accuracy of the model without increasing the computational complexity of the model. In addition, since the focus of the network is on areas with large deformation differences, the training speed can be accelerated to a certain extent.

3. EXPERIMENTS

3.1. Dataset
The paper uses a public standard data set\[9\], which contains 435 frames of 20 MHz IVUS B-mode images. The dataset consists of IVUS images of 10 different patients. The data acquisition system is a Si5 device equipped with a 20 MHz Hawkeye monorail catheter. Each image is 384*384 pixels and contains the corresponding inner and outer contour coordinate labels manually annotated by experts. The expert labeling of the inner and outer membranes is conducive to accurately extracting the ROI area, and eliminating manual extraction errors. In this paper, the data after simple preprocessing will be subjected to varying degrees of elastic deformation to achieve data expansion operations. The final experimental data includes 1550 pairs of images, of which 1500 pairs are used as the training set and 50 pairs are used as the test set.

3.2. Implementation
The Anaconda 3 is used to create a PyTorch model runtime environment. The registration network model is built on Pycharm software. The initial value of the network weight is set to a uniform random value between [-1, 1], the learning rate is set to 0.001, the training batch size is 15, $w_1$ is set to 0.2, $w_2$ is set to 5. The values of $w_1$ and $w_2$ are determined after many experiments. The experiment was trained on NVIDIA GTX 1080Ti GPU and optimized by the ADAM optimizer.

4. Results
4.1. Qualitative experiment
The experiment selects IVUS image pairs in the test set. The results show the registered images. In addition, the registered images and the pre-registration images are superimposed with color channels for qualitative analysis. Figure 3 shows the registration results of two IVUS images from three different patients, and each row represents a set of experimental results. Column (a) shows the fixed image $I_F$; column (b) shows the moving image $I_M$; column (c) shows the registered image $I_M(\phi)$ by the proposed method; column (d) shows the contrast effect of the superimposed color channels of $I_F$ and $I_M$. Among them, $I_F$ is the blue channel image, $I_M$ is the red channel image. The overlapping area of the two images displays purple, and the non-overlapping area displays the color of the corresponding basemap; column (e) shows the contrast effect of the superimposed color channels of $I_M$ and $I_M(\phi)$. Among them, $I_M$ is the blue channel image, $I_M(\phi)$ is the red channel image, and the overlap of the two images shows the same effect as above; column (f) shows the contrast effect of the superimposed color channels of $I_F$ and $I_M(\phi)$. Among them, $I_F$ is the blue channel image, $I_M(\phi)$ is the red channel image, and the overlap of the two images shows the same effect as above.
Figure 3 Registration results of IVUS images
((a) Fixed($I_F$); (b) Moving($I_M$); (c) Moved($I_M(\phi)$); (d) $I_F+I_M$; (e) $I_M+I_M(\phi)$; (f) $I_F+I_M(\phi)$))

From the column (d) of Figure 3, it can be seen that the two IVUS images have local displacement changes in multiple different regions of the inner and outer membranes. The $I_F$ and $I_M(\phi)$ images of the three experiments in column (f) of Figure 3 have a high degree of overlap. The overall color is purple, which means $I_M$ registration is very close to $I_F$. The propose method has a good registration effect on the displacement changes of the inner and outer membranes of intravascular ultrasound images.

4.2. Quantitative experiment
This paper uses DC (Dice Coefficient) coefficient and HD (Hausdorff Distance) coefficient for quantitative evaluation. In order to further verify the proposed model, this paper compares it with the Voxelmorph and Ants methods. Table 1 shows the experimental results of different methods in the standard data set.

|                              | lumen  | media  | HD/mm  | GPU/sec | CPU/sec |
|------------------------------|--------|--------|--------|---------|---------|
|                              | DC     | HD     | lumen  | media   |         |
| ANTs                         | 0.718±0.162 | 0.686±0.153 | 0.32±0.12 | 0.45±0.24 | - | 9863 |
| Voxelmorph (CC)              | 0.656±0.132 | 0.638±0.102 | 0.45±0.03 | 0.58±0.35 | 1.5 | - |
| Voxelmorph (MSE)             | 0.680±0.112 | 0.652±0.135 | 0.39±0.17 | 0.49±0.21 | 1.5 | - |
| Ours (CC)                    | 0.702±0.107 | 0.667±0.128 | 0.36±0.23 | 0.55±0.23 | 1.5 | - |
| Ours (MSE)                   | 0.707±0.118 | 0.671±0.162 | 0.35±0.13 | 0.47±0.22 | 1.5 | - |

It can be seen that the method proposed in this paper has obvious advantages compared with these methods.

5. Conclusions
This paper presents an intravascular ultrasound image registration method based on unsupervised learning to detect changes in the inner and outer layers of blood vessels. Different from the method based on supervised learning, the algorithm in this paper can directly use the training image set for training without obtaining a large number of ground truth values. In the registration network, an attention gate mechanism is introduced to focus the model learning on areas with large marginal morphological
differences to improve registration accuracy. In the loss function, a bending penalty regularization term is added based on the first-order penalty regularization, and the model trained by adjusting the weight values of the two regularization terms can obtain a smoother non-folding DVF. The qualitative and quantitative results show that this method can obtain registration accuracy similar to traditional image registration, but the execution speed increases exponentially.

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