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EXAMINATION OF MEDICAL IMAGE RECORDING ACCORDING TO THE CATEGORY OF RESEARCH PROGRESS AND TECHNICAL METHODS BASED ON DEEP LEARNING

Summary

With the development of imaging-guided surgery and radiotherapy, the clinical demand for medical image matching research is stronger and the challenges are even greater. In recent years, deep learning, especially deep convolution neural networks, has made excellent achievements in medical image processing, and the research on medical image matching has developed rapidly. In this paper, the domestic and foreign research progress based on deep learning medical image alignment is summarized according to the classification of technical methods, including the similarity estimation based on optimization strategy, the transformation parameters of direct estimation of medical image alignment, etc. Then it analyses the challenge of the deep learning method in medical image matching and puts forward possible solutions and research directions.

Key words: *medical image recording, deep learning, CNN, full convolutional network*

1. Introduction

There are various types of medical images, such as X-ray, ultrasound (US), computed tomography (CT), magnetic resonance imaging (MRI) and positron emission tomography (PET). The medical image alignment refers to the analysis of the medical image. Medical image alignment refers to the establishment of correspondence between two or more images, where each image is brought into the same coordinate system through various transformation models, and the same anatomical point on the human body has the same spatial position of the two or more matched images. For image-guided radiotherapy, radiosurgery, minimally invasive surgery, endoscopy, interventional radiotherapy, etc., image alignment is one of the key technologies for paramedicine. For unimodal medical image alignment (alignment of the same type of medical images), for the same patient, medical image alignment at different time periods can compare the growth of lesions and analyze the treatment effect. For different patients, the alignment of images can assist in the diagnosis of the disease. For multimodal medical images (alignment of different types of medical images), the combined use of information from multiple imaging devices and multimodal image alignment before and during surgical procedures can help to precisely locate lesions and assist in radiation treatment planning.

Existing medical image alignment methods include two main types: grayscale-based methods and feature based methods. The common grayscale-based methods include intercorrelation method, sequence similarity alignment method, mutual information method, etc. Grayscale based methods can be used for rigid and non-rigid alignment with high alignment accuracy but are plagued by problems such as flatness of the maximum value of the similarity metric, monotonic texture, and high computational complexity. The core steps of feature-based image alignment methods are feature extraction, feature matching, model parameter estimation, image transformation and grayscale interpolation. Features are divided into point features, line features, and surface features, etc. The classical alignment method is to extract features by scale invariant feature transform (SIFT) or speed up robust features (Surf), combined with Random sample consensus (Ransac) algorithm is

used to filter the features and obtain the coordinates of matched pairs of points so that the image transformation parameters can be calculated. The most important problem faced by traditional alignment methods is that they iteratively optimize the cost function from zero for each image to be aligned, which severely limits the speed of alignment and ignores the inherent alignment patterns shared between images of the same dataset [1].

In recent years, deep neural networks simulating human brain learning have achieved great success in the fields of image recognition, speech recognition, natural language, and computer vision, and have become one of the hot spots of research. Especially, convolutional neural networks (CNN) have surpassed other methods in computer vision applications such as classification [2], segmentation [3], target detection [4], and other fields. According to the literature [5-12], deep learning is currently excelling in both medical diagnosis and medical image processing applications, such as detecting brain tumors, diabetic retinopathy, nodules in chest films, and determining breast cancer based on X-rays. Using deep neural networks, expert-level diagnosis of individual diseases is possible, such as Esteva et al [13] used it for skin cancer diagnosis; Gulshan et al [14] applied it for automatic detection of diabetic retinopathy and diabetic macular edema. Among them, the research results of Esteva et al [13] were recognized by the ex-Mol knowledge platform (at https://www.x-mol.com/) as one of the top five global breakthroughs in science and technology in February 2017. In medical image alignment, the application of deep learning methods has also made recent progress, and the applied methods include CNN and fully convolutional networks (FCN), which are of great significance for clinical image-guided surgery and radiotherapy.

The research direction of our lab is segmentation and alignment of medical images, and our recent work is mainly focused on the application of deep learning methods in medical image alignment. Shan et al [1] showed that using a fully convolutional alignment framework, the alignment speed is 100 times faster than traditional methods. Using a typical 3D brain image as a dataset, Fan et al [15] investigated the computational cost of seven different deformable alignment algorithms and showed that a deep learning network without any iterative optimization (named "BIRNet" by the authors of this paper) takes the least time. Secondly, there are some improvements in alignment accuracy after applying deep learning methods. For example, Cao et al [16] introduced deep learning methods to the alignment of brain MRI images, and the dice similarity coefficient (DSC) was improved in the alignment of white matter, gray matter, and cerebrospinal fluid, with a maximum improvement rate of 2.6%. This research team has achieved some research results of multimodal image alignment of nasopharyngeal carcinoma, and the accuracy of alignment has been improved by several tens of times compared with the traditional SIFT algorithm. In this paper, we summarize the research progress, analyze its challenges and countermeasures, and propose further research directions for deep learning in medical image alignment.

2. Research progress of deep learning in medical image alignment

There are some limitations in the research of deep learning-based medical image alignment. Shan et al [1] pointed out that "for learning-based approaches: (i) it is difficult to obtain the information feature representation directly by learning and optimizing deformation or similarity functions; (ii) unlike the image classification and segmentation, alignment labels are difficult to collect. These two reasons limit the development of learning-based alignment algorithms". However, researchers have achieved better results in ultrasound and CT image alignment of the spine [17], head CT and MRI image alignment [18], and chest CT image alignment [19]. The deep learning methods proposed in the currently available research results mainly use the CNN and FCN frameworks, especially some methods using the CNN framework.

The classification of research on deep learning for medical image alignment can be classified in terms of the framework of deep learning, or by supervised and unsupervised. In this paper, we classify deep learning according to its framework and discuss supervised and unsupervised deep learning, especially unsupervised deep learning for medical image alignment in the chapter on challenges and countermeasures.

2.1. Research progress on CNN-based medical image alignment

The application of deep learning in medical image alignment is heavily used in CNN models, and CNN regression, which is mostly used in recent years, is a means to solve image alignment by learning methods.

Chen et al [17] proposed the use of CNN for the alignment in 2016, and they presented at the International conference on medical imaging and virtual reality (MIAR): in spinal surgery in image-guided anesthesia, a CNN is used to align 2D ultrasound and 3D CT images of multiple vertebrae (L2 to L4). Specifically, the CNN is used to classify the input images into several pre-calibrated standard sections, and the spatial parameters of the pre-calibrated sections are used to achieve coarse alignment of the images, followed by fine adjustment of the local alignment using mutual information. The method achieves automated intraoperative alignment with an average target alignment error of 2.3 mm, which is lower than the clinically accepted 3.5 mm, but the improvement of the alignment error mainly relies on the tuning using the mutual information method.

2.1.1. Similarity estimation based on optimization strategies

The key to alignment is the selection of an appropriate similarity metric. The methods of similarity metrics include the sum of squared differences, mutual information, and joint entropy, etc. Some researchers have used an iterative optimization strategy to estimate the similarity metric between images using CNN to perform the optimized image alignment metric as a cost function. This task is challenging due to the non-convexity of the matching metric on the space of likelihood alignment parameters. Eppenhof et al [20] proposed a CNN-based supervised estimation method for image alignment error maps. The CNN was trained and validated on a set of 2D digital subtraction angiography sequences, and the CNN was able to learn the alignment errors in 2D alignment images with sub-pixel accuracy. Cheng et al [18] proposed two types of stacked autoencoders to evaluate the similarity between head CT and MRI images, which trained a binary classifier to learn the correspondence between the two image blocks the method trains a binary classifier to learn the correspondence between the two image blocks, converts the classification output to a continuous probability value, and then uses it as a similarity score. In addition, Cheng et al [18] proposed an effective preprocessing of deep neural networks using multimodal superposition denoising autoencoders, and experimental results confirmed the high accuracy and robustness of this metric. Lee et al [22] used CNN regression to model a sequence of motion actions for 3D alignment, which took 3D raw image data as input and the next optimal action as output and modeled the patient's cardiac CT and X-ray tomography images (cone beam computed tomography (CBCT), abdominal spine CT, and CBCT 3D images of patients. They reduced the image alignment problem to a "strategy, learning" process, using reinforcement learning to predict iterative updates of the alignment with the goal of finding the best sequence of motion actions to produce the image alignment, but it is important to note that this approach is only applicable for rigid body transformations.

2.1.2. Direct estimation of transformation parameters for medical image alignment

In CNN regression alignment methods based on optimization strategies, deformable alignment methods require exhaustive iterative optimization and parameter tuning to estimate the deformation fields between images. Although previous studies have proposed some learning-based initial deformation estimation methods, they are often template-specific and not flexible in practical applications. Co et al [16] proposed a CNN-based regression model that directly learns a complex mapping from input image pairs to the corresponding deformation fields and obtained good alignment performance by experimenting on different brain image datasets. Miao et al [23] proposed to use CNN regression to directly estimate the transform parameters for medical image alignment. In the 2016 IEEE transactions on medical imaging (TMI), Miao et al [23] used a deep learning approach for 2D X-ray-3D, CT medical image alignment to evaluate the pose and position of implanted objects during surgery. A deep learning approach for 2D X-ray-3D, CT medical image alignment was used by Miao et al [23]. It uses a CNN regressor to predict the transformation matrix for rigid alignment of

2D and 3D images, addressing two major drawbacks of existing grayscale based 2D/3D alignment techniques: ① Slow computational speed. Because re-rendering needs to be done every time the spatial transformation parameters are updated; (ii) the capture range is small. They parameterize the feature space into two corner parameters in 20-degree order and train a separate CNN to predict the update of the transformation parameters. A fixed number of k blocks of region of interest are input to the CNN separately to generate feature vectors, which are then connected first and last, followed by two fully connected layers, and finally input to the regressor. This method is highly accurate, has large capture range and real-time, and has been well evaluated in clinical applications. However, their models cannot be deformable aligned.

In addition to the CNN regression approach, Sokooti et al [19] proposed an end-to-end CNN-based method to directly predict the 3D non-rigid displacement vector field (DVF) of a given fixed or motion image. Society et al [19] named the designed a C N The alignment accuracy of this method on 3D chest CT images are comparable to that of the conventional b-spline method. Codec network to initialize the momentum of the large deformation diffeomorphic metric mapping (LDDMM) alignment model using an open, accessible series of imaging studies (OASIS) of the brain. Studies (OASIS) to experiment with the alignment of MRI images of the brain. The experiments show that the method can accurately predict the alignment results obtained by numerical optimization fast, with a 1500-fold speedup in 2D and a 66-fold speedup in 3D compared to other experiments that obtained similar results. However, the method requires some post-processing outside the CNN network.

2.1.3. Studies on medical image alignment for small samples

Supervised deep learning methods generally require a large annotated clinical dataset for training, while the sample size of medical images is generally small, to address this situation, Zheng et al [25] proposed a pairwise domain adaptation (PDA) module that adapts the trained model from the source domain (i.e., synthetic data) to the target domain (i.e., clinical data) by learning domain invariant features. The PDA module can be inserted into any pre-trained CNN model and can adapt to different deep network frameworks. The modeling capabilities of CNNs have been used to improve the accuracy and efficiency of accurate alignment of preoperative 3D data and interpretive 2D X-ray images. Uzunova et al [26] proposed a new method for learning representative shape and appearance models from a small number of training samples and embedded it in a new model-based data augmentation scheme to generate a large amount of training data, solving the problem of CNN for medical image alignment after learning from only a small amount of training data.

2.1.4. Other studies

Wu et al [27] performed alignment of brain MRI images, and they added an unsupervised learning process before the CNN so that the model could automatically learn data features. Specifically, Wu et al [27] constructed a superimposed two-layer CNN network to find a representation of each image block, where the high-level features are inferred from the responses of the lower-layer network. The learned adaptive features were used instead of hand-designed features for image alignment, and good alignment results were achieved. However, they are also a block-based learning system and rely on other feature-based alignment methods for image alignment.

Optical flow (optical flow) is a method that uses the change of pixels in the image sequence in the time domain and the correlation between adjacent frames to find the correspondence that exists between the previous frame and the current frame to compute the motion information of the object between adjacent frames. Uzunova et al [26] improved the structure of optical flow neural network (named: FlowNet) by The CNN was integrated into the optical flow alignment method and applied to the medical image alignment problem based on CNN optical flow estimation.

2.2. Research progress of FCN-based medical image alignment

The application of FCN in medical image segmentation is relatively common, but the application in medical image alignment is still relatively small. At present, FCN is mainly used in FCN has been applied to the alignment of cardiac CT images and 3D brain structure MRI images. Marc-Michel et al [28] proposed a new method based on the prediction of two image parameters using their Marc-Michel et al [28] proposed a new alignment method based on the prediction of two image parameters using their designed FCN (which differs from the standard FCN) for 3D cardiac CT images, the network can detect global features that cannot be detected by the sliding window method. The network can detect global features and deformations that cannot be detected by the sliding window method. The network can detect global features and deformations that cannot be detected by the sliding window method, and it takes less than 30ms to align the two 3D images on the graphics processing unit (GPU). It takes less than 30ms to align two 3D images on the graphics processing unit (GPU).

Due to the limited sample of medical images and the difficulty of labeling, researchers have been hoping to improve the quality of the data set. Researchers have been hoping to make a breakthrough in deep learning methods that are less demanding on data sets. The breakthroughs in deep learning methods have been expected to be less demanding on data sets. Self-supervised learning can generate Li et al [29] applied FCN for self-supervised non-rigid image alignment, using known spatial transformation training data to learn spatial transformations. It is like the traditional image alignment algorithm by directly estimating the image similarity between pairs of images through the image similarity measure with the deformed motion image. Li et al [29] used the spatial transformations between image pairs to estimate the spatial transformations directly from the image similarity measure between the deformed motion images. Li et al [29] conducted experiments on a 3D brain structure MRI image set, and the trained FCNs were used to estimate the spatial transformation between image pairs by the feedforward calculation of FCN. The trained FCNs can be aligned with new images through feedforward computation of FCNs.

3. Challenges and countermeasures

3.1. Challenges and countermeasures for medical image samples

3.1.1. Sample problem

Deep learning is used for the analysis of medical images. Deep learning for medical image analysis has three difficulties in terms of samples: (i) the sample size is small, and it is difficult to share samples due to privacy and other It is difficult to share samples due to privacy issues. (2) The samples need to be annotated by experts, which is time-consuming and costly; (3) the samples are unbalanced, and the pathological samples are small.

Three countermeasures are available to address these problems. For the supervised deep learning, researchers have proposed sample enhancement approach and migration learning approach. In addition, researchers have also proposed unsupervised learning methods.

3.1.2. Sample augmentation

For sample augmentation, Chen et al [30] summarized six types of data augmentation methods, as follows.

(1) Learning a learning model with one labeled sample (one-shot) using the stream information of a large amount of unlabeled data.

(2) Adaptively learning classification, samples from a pre-trained model [31-32].

(3) Borrowing examples of relevant categories or semantic vocabularies to expand the training set [33].

(4) Synthesize new labeled training data. Chen et al [30] proposed a new dual, triple net autoencoder network for feature enhancement. The encoder projects the multilayer visual features of the deep CNN in the semantic space. Because there is richer information on the semantic space, data

expansion can be done on the semantic space, and the enhanced instance representation is mapped back to the image feature space by the decoder to obtain more expanded samples.

(5) Generating new examples using generative adversarial networks (GAN) [34-36].

(6) Attribute-guided augmentation (AGA) method, which enables the synthesis of samples based on the expectation or intensity. That projects images into an attribute space and generates artificial samples to extend the given training data set; it performs data augmentation in the feature space rather than the image space.

3.1.3. Migration learning

Another experimentally validated and effective method for the case of insufficient samples is transfer learning, i.e., transfer learning coupled with fine tuning can be used to solve the difficulties of medical image datasets, according to which the group in this paper has conducted this research. First, we investigate how fine-tuning a pre-trained CNN can achieve good image processing performance in a hierarchical manner [38]. The group uses a pre-trained CNN as a feature extractor, pretrains the CNN by using a natural image library (called "Imagenet") containing a large amount of labeled data, uses the pre-trained CNN parameters as the initial values of the supervised learning network, and uses a limited number of professional image annotation the learnable parameters in the pre-trained CNN are tuned using a limited set of professional image annotation data. Fine-tuning the second half of the layers of the network during migration learning training, they can achieve almost the same accuracy, but faster convergence compared to fine-tune the whole network. Shin et al [39] also investigated migration learning combined with fine-tuning to show when and why fine-tuning of networks pre-trained through the imagined natural image library is useful, and their approach was to fine-tune all layers except the last one at a learning rate 10 times smaller than the default learning rate, and the results were validated by thoracoabdominal lymph node detection, but it is still challenging to determine the optimal learning rate for different layers.

3.1.4. Unsupervised learning

Labeling of medical samples is costly and difficult to obtain, while it is much easier to obtain a large amount of unlabeled medical data. Considering the uniqueness of medical images and the high cost of labeling, unsupervised learning is an important research direction. So far, supervised models have mostly outperformed unsupervised models and there are relatively few research results on unsupervised learning, but there is a great desire to develop an unsupervised, end-to-end CNN framework for medical image alignment.

In 2015, Jaderberg et al [40] proposed a new learning module, spatial transformer (ST), that allows the network to explicitly exploit the spatial information of the data. This derivable module can be inserted into existing CNNs, allowing the CNN to have invariance to translations, scale transformations, rotations, and common distortions without additional training, and to be able to perform image alignment without supervised labeling. In a subsequent study, the ST module was used in conjunction within subsequent studies, progress has been made in unsupervised medical image alignment using a combination of ST modules and other networks. De Vos et al [41] proposed a deformable image alignment (named "DIRNet" by the authors), which consists of a CNN regressor, a spatial regression DIRNet consists of a CNN regressor, a special transformer, and a replayer. Dragnet performs unsupervised optimization of the similarity metric between input image pairs. The alignment accuracy of DIRNet of cardiac MRI images is the same as that of the traditional deformable image alignment method and has a better performance than the traditional deformable image alignment method. The accuracy of DIRNet for aligning cardiac MRI images is the same as that of traditional deformable image alignment methods, with a shorter execution time.

The method of the Vos et al [41] has the drawback of supporting only small transformations on a limited set of volumes. To be suitable for handling large deformations, Balakrishnan, et al [42] recently combined CNN with ST and made further improvements. They defined alignment as a parametric function, modeled the function using a CNN, and reconstructed the image from another

image using a spatial transformation layer while imposing smoothing constraints on the alignment domain. This approach is not only unsupervised does not require a large amount of annotated data, but also greatly speeds up the process.

In addition to incorporating the ST module, the approach proposed by Shan et al [1] transposes the traditional image alignment algorithm to an end-to-end CNN framework while maintaining the unsupervised nature of the image alignment problem. Used for medical image alignment of 2D liver CT/MRI and brain CT/MRI, the alignment is 100 times faster than traditional methods, and the method can be extended to other organs beyond the liver and brain, such as kidney, lung, and heart.

In addition, in 2014, GAN was introduced. The network architecture of GAN is disruptive in that it creates a generative network and a discriminative network at the same time, and the network can be trained end-to-end and learn representative features in a completely unsupervised manner, which provides a research direction for a technical solution for unsupervised alignment of medical images.

3.2. Challenges and countermeasures for multimodal medical image alignment

In addition to unimodal image alignment, due to the high variability of tissue morphology in different imaging modalities, there is a clinical need for multimodal medical image alignment, where imaging techniques complement each other's strengths. In grayscale based multimodal image alignment methods, the correlation between grayscale values of related pixels is complicated. Lam et al [12] pointed out that mutual information is a standard similarity measure for multimodal image alignment, but its performance degrades when the image contains local intensity variations, and the mutual information only considers the intensity information in the image and ignores spatial information. Among the feature-based alignment methods, some achievements have been made in multimodal image alignment, such as Chen et al [17] achieved alignment of 2D ultrasound and 3D, CT images of multiple vertebrae (L2 to L4); Miao et al [23] achieved alignment for 2D X-ray images and 3D CT medical images; Cheng et al [18] proposed two types of stacked autoencoders to evaluate the similarity of head CT and MRI images. However, the extraction of identical and variable features in multimodal images is still an important research area. In clinical image-guided surgery, correlating the contrast information on different types of medical images is a challenging task in multimodal image alignment. In image-guided surgery, multiple scans of the patient's organs using different imaging modalities create difficulties in identifying the patient's position and orientation for different imaging systems, thus necessitating the development of more advanced alignment methods to facilitate the elimination of differences in patient positioning [12].

4. Conclusion

Image-guided surgery and radiotherapy have created a strong clinical need for medical image alignment research has created a strong clinical need, and in recent years deep learning has been the application of deep learning in medical image alignment has also developed rapidly in recent years. This paper categorizes the research progress of medical image alignment based on deep learning, and further analyzes the challenges and solutions. This paper categorizes the progress of medical image alignment based on deep learning, and further analyzes the challenges and countermeasures. Whether it is supervised or unsupervised learning, deep supervised learning or unsupervised learning, there is still a wide range of research on deep learning in medical image alignment. There is still a wide scope of research in medical image alignment, both supervised and unsupervised learning. In the clinical setting, for the study of unsupervised learning for preoperative and intraoperative medical image alignment is very in the future, in addition to unsupervised medical image in the future, in addition to the important direction of unsupervised In addition to the important direction of unsupervised medical image alignment, there are also the following interesting research directions.

(1) Automatic annotation of datasets. In medical image alignment, it is important to annotate the data by automatic methods. In medical image alignment by automatic methods is fast but depends on deep learning methods. For example, Chen et al [30] proposed to use the semantics of each class to directly synthesize instance features. Uzunova et al [26] proposed a CNN-based based deep

learning method proposed by Uzunova et al [26], generates a set of training images from a small number of sample images with known correspondences, which can be used to synthesize many medical image alignment training data with annotations. In the automatic annotation process, there are still problems to be solved, such as how to apply deep learning method to efficiently label the dataset, reduce labeling noise and labeling costs, etc. (2) Clinical applications.

(2) Clinical applications. To move towards clinical applications, there are still many Although deep learning has accelerated the computational speed of medical image alignment, there are still a lot of problems that remain to be solved. Although deep learning has accelerated the computational speed of medical image alignment and provided the possibility of real-time alignment Although deep learning has accelerated the computational speed of medical image alignment, providing the possibility of real-time alignment. However, clinical data are always affected by the strong consistency of noise, motion, and uniformity. The image guidance procedure has tissue or small object the phenomenon of tissue or small object occlusion in image-guided surgery, and the possibility of low-quality functional images All of these pose challenges for medical image alignment. In a surgical guidance system, these challenges need to be addressed. In a surgical guidance system, these challenges need to be addressed to align and translate points in the image and improve the probability of correct target registration error (TRE), especially in the case of non-rigid in addition, in surgical procedures, the probability of correct target registration error (TRE) can be improved since the tissues are not properly aligned more accurately. In addition, during surgery, due to tissue deformation, patient and device displacement, the probability of correct target registration error (TRE) is increased. The alignment of the corrected preoperative and intraoperative images needs to be performed when correcting for tissue deformation, patient, and device displacements, etc. The automatic alignment is required to correct the preoperative and intraoperative images without interrupting the operation. Therefore, automatic alignment, especially the multimodal automatic alignment, is Therefore, automatic alignment, especially the multimodal automatic alignment, is a clinically relevant research direction. Automatic image alignment methods the accuracy of the automatic image alignment method depends largely on the accuracy and optimization of the algorithm. Accurate selection of 3D landmarks, accurate extraction of the same features in multimodal images the correct selection of 3D landmarks, accurate extraction of the same features in multimodal images, etc. are challenges for automatic alignment [12].

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