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Deep Learning-based fMRI: A Review

Yifan Cao, Meili Lu*, Jiajun Fu, Zhaohua Guo, Zicheng Gao

School of Information Technology Engineering, Tianjin University of Technology and Education, Tianjin 300222, China

*E-mail: meililu@tute.edu.cn

Abstract

Functional magnetic resonance imaging(fMRI) is a non-invasive technique for the study of brain function that has been developed in recent years. The advent of this technique has allowed researchers in related sciences to directly observe changes in the brain during inverted resting states and various behavioural states, which has given researchers the opportunity to learn more about brain information. At the same time, as science and technology develop, deep learning techniques are increasingly being used in this field. In this paper, we will briefly discuss recent advances in the combination of deep learning and fMRI techniques.

Keywords

Brain Image; Deep Learning; Functional Magnetic Resonance Imaging.

1. Introduction

The term 'Deep Learning' (DL) was first introduced into Machine Learning (ML) in 1986 and later used in Artificial Neural Networks (ANN) in 2000. Deep neural networks consist of multiple hidden layers to learn features of data with multiple levels of abstraction, and the DL approach allows computers to learn complex concepts through relatively simple ones. For artificial neural networks (ANNs), deep learning (DL) (also known as Hierarchical Learning), in order to learn complex features, deep architectures are used at multiple levels of abstraction, i.e. non-linear operations; ANNs, for example, have many hidden layers. To summarise in precise terms, deep learning is a subfield of machine learning that uses multiple levels of non-linear information processing and abstraction for feature learning, representation, classification, regression and pattern recognition in supervised, unsupervised, semi-supervised, self-supervised, weakly supervised and so on.

fMRI is a functional magnetic resonance imaging technique based on magnetic resonance imaging (MRI), a tool that uses the phenomenon of magnetic resonance to obtain electromagnetic signals from the body and then reconstruct information about the body based on these signals. This technique is more versatile and complex than other imaging techniques (such as computed tomography (CT), positron emission computed tomography (PET), etc.), which makes it possible to obtain a greater wealth of information. However, because of some of the disadvantages of MRI, such as delayed signals due to magnetic field inhomogeneities, researchers have further developed fMRI. fMRI differs from MRI in that it requires the acquisition of MRI images over a period of time and then observes changes in brain imaging over that period.

Since its inception, fMRI has become the darling of functional brain imaging techniques, with countless researchers involved over the decades and close to 100,000 papers addressing the technique as of 2021. The reason for this is undoubtedly the ability of fMRI to detect the structure of the brain and its dynamic changes.

The most important organ in the human body is undoubtedly the brain, so studying the human brain has always been a worthwhile endeavour, but there are side effects to be aware of. fMRI technology can pinpoint specific cortical areas of brain activity and can also track changes in signal in real time. As the technology has evolved, it is now used in a wide range of fields such as medicine, and in some scenarios it can also help to identify the images seen by the research subject. Today, fMRI data is widely used because it is a time-series based 3D brain imaging data and its temporal characteristics are important for the task of classifying the cognitive state of the brain.

In summary, this paper will tan'ta the currently popular research combining fMRI and deep learning methods.

2. Functional Magnetic Resonance Imaging

The processes of fMRI pre-processing are generally: visualisation, artefact removal, temporal calibration, head-motion calibration, structure-function alignment, normalisation and time-space filtering.Visualisation: The first step in pre-processing, only after the original image has been visualised can you look at what is wrong and target it for processing.

Artifact removal: Artifacts are images that do not belong to the body that appear during MRI scanning or image processing. When the acquired information is disturbed by external noise, the image does not correctly reflect the state of the subject itself, which means that artefacts are created. There are two common types of artifacts: Ghost artifacts, head movement artifacts, blood flow artifacts and physiological artifacts. For head artifacts, Chen Yulin and others in China have proposed a blade artifact correction technique to eliminate artifacts. For blood flow artefacts, the images can be processed by using fMRI and MRI fusion techniques to effectively eliminate blood flow artefacts. For physiological artefacts, which can be caused by physiological activity such as breathing and heartbeat, there are several solutions such as digital filtering, K-space estimation and correction, and retrospective correction.

Temporal calibration: Because most of the time multiple brain slices are scanned in one sequence during a single scan cycle, there is a relative delay in the signal on all the slices recorded, so we need to account for temporal differences.The most common way to obtain data for the same time point for different slices is by interpolation, which is used to predict the value of a location point from the signal value of a known point adjacent to an unknown point.

Head calibration: When fMRI is used for data acquisition, if anything produces serious interference, it is undoubtedly because of the subject's head movements. We therefore used a rigid transformation to fix all the brains in the images at the same target position. As far as possible, our processed images were made to match the target images, with a cost function representing the similarity between the two.

Structure-function alignment: Structure-function alignment is the alignment of the structural image to the functional image, where we acquire an image that may not be of high enough resolution to be localised to an image with high resolution.

Standardisation: Because everyone's physical features are not identical, the structure of the brain is not identical, and in many cases it is very different. So we have to standardise, by stretching, compressing and coiling the scanned brain to match a predetermined template. By normalising we can generalise the results of the experiment, although this may also lead to a reduction in the final spatial resolution.

Spatial filtering: Spatial smoothing of the acquired data helps us to go about improving the signal-to-noise ratio and removing artefacts.

3. Deep Learning

With the development of technology, machine learning is also progressing. For example, the short videos and songs recommended by various video and music apps on users' mobile phones use recommendation systems that filter and filter the data through clustering techniques and then push the information that best matches the user's historical habits to the user. The technology has also come a long way in the last few decades for recognising handwritten numbers, recognising images or converting speech to text. In recent years, the analysis of neuroimaging data has increasingly been applied to machine learning, and naturally researchers have begun to link fMRI and EEG techniques to the most popular machine learning techniques. This is because traditional machine learning techniques such as support vector machines (SVMs) are very labour intensive in terms of the feature engineering that is constructed when processing these large data. Deep learning, a subfield of machine learning, has made great progress over the years, and more and more methods from related fields are being applied to the analysis of fMRI and EEG data.

Deep learning is a process of learning from simplicity to complexity by combining simple but non-linear modules, each of which transforms a low-dimensional representation into a higher-dimensional one, and when enough of these transformations are made, complex functions can be learned and well-performing models can be built. Currently, the most popular models used in the field of deep learning are neural networks, and this paper will briefly introduce two of the most popular models that can be combined with the two techniques described above: convolutional neural networks and recurrent neural networks.

Neural networks: it is originate in the human brain. The material basis for human thinking is the human brain, and the function of the human brain lies in the cerebral cortex. In the human cerebral cortex there are about 10^11 neurons, each of which is connected to other neurons through synapses, thus forming a highly complex network. An artificial neural network is a network model that is simulated in a computer and then used to solve practical problems.

Neural networks consist of interconnected layers, like the structure of the human brain, which can learn from large amounts of data and then be used to solve real-world problems. The basic components of a neural network are neurons, each of which is equivalent to a processing unit. Each set of neuron connections is weighted to simulate synapses in the cerebral cortex. The neurons in each layer receive the weighted information, process it through some activation function (like relu, tahn, etc.) and pass it on to the next layer until the output is ready.

Feed-forward Neural Networks:it is a network model that allows only a positive flow of information, in which decisions depend on the current input, are not recorded for too much data and are generally used for classification and regression. The technique most often associated with fMRI and EEG techniques today is a particular type of network within feedforward neural networks: convolutional neural networks. Its origins can be traced back to the neocognitron model proposed by the Japanese scholar Kunihiko Fukushima in the last century, a neural network with a deep structure that is considered to be one of the first deep learning algorithms. The first real CNN was the time-delay network proposed by Alexander et al. in 1987, which was applied to speech recognition, with the first two one-dimensional convolutional kernels in its hidden layer, which were used to extract translational invariant features in the frequency domain. CNNs have since flourished and have been used in a variety of applications: speech recognition, image recognition and detection of medical impact, to name a few. In recent years, large-scale complex CNNs have achieved impressive success, with algorithms such as GoogLeNet and ResNet achieving spectacular error rates.

CNNs add a convolutional layer to a feedforward neural network, allowing the entire network model to be trained better than before. The basic CNN consists of a convolutional layer and a pooling layer. The final output of the CNN is a specific feature space for each image, which is later used as the input to the fully connected layer.

Recurrent Neural Networks:The RNN is a specific type of neural network that can be traced back to the reverse circuit hypothesis proposed by the Spanish neurobiologist Rafael in the 1930s. This hypothesis was found in the anatomical structure of the cerebral cortex in neural circuits that allowed for the cyclic transmission of stimuli, and this hypothesis was thought to be the reason why organisms have short-term memory . With the development of neurobiology, the modulation of the reverse circuit by the brain's alpha rhythm sought to become a cyclic feedback system in the alpha-motor nerve . And in the 1980s, RNNs began to develop rapidly, which include Elman networks, SRNs and RTRLs , etc. In the twenty-first century, with the development of deep learning theory and technological advances, RNNs are playing their role in more and more fields.

4. Discussion

Despite the great success of deep learning in many areas, it still has a long way to go. There is still a lot of room for improvement. As far as limitations are concerned, examples are quite numerous. For example, Nguyen et al. show that deep neural networks (DNNs) can be easily spoofed when recognising images. There are other issues, such as the transferability of features for learning as proposed by Yosinski et al. Huang et al. propose an architecture for defence against neural network attacks, arguing that future work will need to defend against these attacks, while Zhang et al. propose an experimental framework for understanding deep learning models, and they argue that understanding deep learning requires rethinking and generalisation.

5. Conclusion

Although deep learning (DL) is advancing the world faster than ever before, there are still many aspects that deserve to be investigated. We still don't fully understand deep learning and how we can make machines smarter, closer to or smarter than humans, or learn like humans. dL has been solving many problems while applying the technology to all aspects. But there are still many challenges facing humanity, such as people still dying from hunger and food crises, cancer and other deadly diseases. We hope that deep learning and artificial intelligence will be more dedicated to improving the quality of human life by conducting the most difficult scientific research. Last but not least, may our world become a better place.

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