An overview of the possibilities of combining medical imaging with deep learning techniques focused on CT

Przegląd możliwości połączenia obrazowania medycznego z technikami głębokiego uczenia skupionym na TK

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Introduction

We first encountered deep learning in medical imaging in 2016, when the article "Deep Learning in Medical Imaging" was published in the journal IEEE Transactions on Medical Imaging [1]. Over the years, more papers have confirmed the initial impact of deep learning on medical imaging. Deep Learning is one of the 10 breakthrough technologies of 2013. The impact of machine learning in the future should play a significant role in the field of imaging, both medical and industrial imaging. In this work, we will explore the field of biomedical imaging. Biomedical imaging can be divided into two important components: image reconstruction and image processing and analysis. Currently, there is still great scope to investigate the application of machine learning for image reconstruction. The figure (Fig. 1) shows the use of machine learning techniques in recent years.

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Abstract

Combining tomographic imaging with deep learning techniques enables image analysis. There are still many questions in the subject of image reconstruction from projection using a deep neural network. This publication focuses on biomedical imaging with an emphasis on developing a new generation of image reconstruction techniques using deep neural networks. Such targeted research may lead to the development of intelligent use of knowledge in big data, including innovative approaches to the reconstruction of tomographic images and further development in the area of diagnostic imaging. Fully utilizing the possibilities of machine learning in biomedical imaging will be the first step in the development of new translational techniques.

Key words: computed tomography, CNN, deep learning, image analisis

Streszczenie

Połączenie obrazowania tomograficznego z technikami uczenia głębokiego umożliwia analizę obrazu. W dziedzinie rekonstrukcji obrazu z projekcji za pomocą głębokiej sieci neuronowej wciąż istnieje wiele wątpliwości. Ta publikacja skupia się na obrazowaniu biomedycznym z naciskiem na opracowanie nowej generacji technik rekonstrukcji obrazów właśnie z użyciem głębokich sieci neuronowych. Tak ukierunkowane badania mogą prowadzić do rozwoju inteligentnego wykorzystania wiedzy z zakresu big data, w tym innowacyjnych podejść do rekonstrukcji obrazów tomograficznych oraz dalszego rozwoju w obszarze diagnostyki obrazowej. W pełni wykorzystane możliwości uczenia maszynowego w obrazowaniu biomedycznym będzie pierwszym krokiem do rozwoju nowych technik translacyjnych.

Słowa kluczowe: tomografia komputerowa, CNN, głębokie uczenie, analiza obrazu

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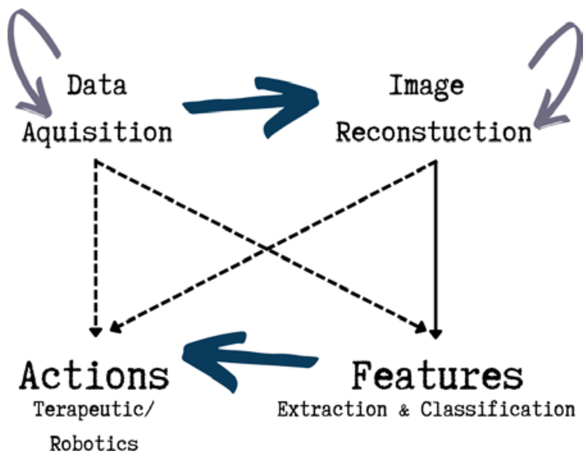

Fig. 1 Figure showing biomedical imaging and deep learning
Source: Own implementation.

In the next chapter we discuss the importance of the neural network for image reconstruction. Further we discuss specific issues that will allow appreciating the operation of deep neural networks in biomedical imaging. In the final chapter of the work, we discussed deep imaging, formulated paradigm shift statement, and draw conclusions.

Justification for using deep learning for reconstruction algorithms

The human nervous system consists of billions of neurons [2]. Neuroscience as an interdisciplinary field sees the human brain as a "supercomputer" [3]. Many attempts have been made to make computers as fast as the human brain. Computing power has increased dramatically over the past 20 years. This enabled the creation of models with detailed anatomical connections with realistic physiological parameters. Over time, large-scale brain simulation has become a milestone in computational neurobiology. Therefore, modern and efficient computational technologies have been introduced to research in neuroscience.

The ANN (Artificial Neural Network) approach appeared two decades ago, but it did not attract much public interest. One of the most critical voices of neural networks was the need to use a lot of computing power and have a large amount of data. Another problem was how to solve long training how to solve the problem of long training of the neural network, which scales poorly with the size of the network. The complexity of the problem led to fixing the data at the local extreme. A real milestone came with the unsupervised learning procedure for the limited Boltzmann machine. This procedure can be used recursively to prepare a deep network layer by layer. Trained neural network parameters can be tuned using the backpropagation method. Currently, the successes of deep networks are known in such areas as computer vision, speech recognition, and classic computer games.

In the deep network, there are many layers of neurons with inter-layer connections. Initially, data is entered into the input layer, and then the weights related to the network training process are appropriately transformed in the training process. A large collection of tagged and untagged images is used. The training results are obtained at the output layer of the network. Lower layers analyse lower-level features, such as image edges, whereas upper layers analyse features of the higher level. Thanks to innovative algorithm-building components, this deep learning engine has proven to be extremely effective at feature extraction[4]. In computed tomography, we are interested in obtaining this projection data, from direct measurements to tomographic images. Raw data is treated as image features that are linearly approximated to the image voxel value. The reconstruction of the tomographic image starts from raw data, i.e. the features of the measured data by scanning with a computed tomography apparatus. This is essentially the opposite of pattern recognition which moves from images to features. The reverse process is not a conceptual challenge, but in some cases, this is where the research to reconstruct an image using deep neural networks begins [5].

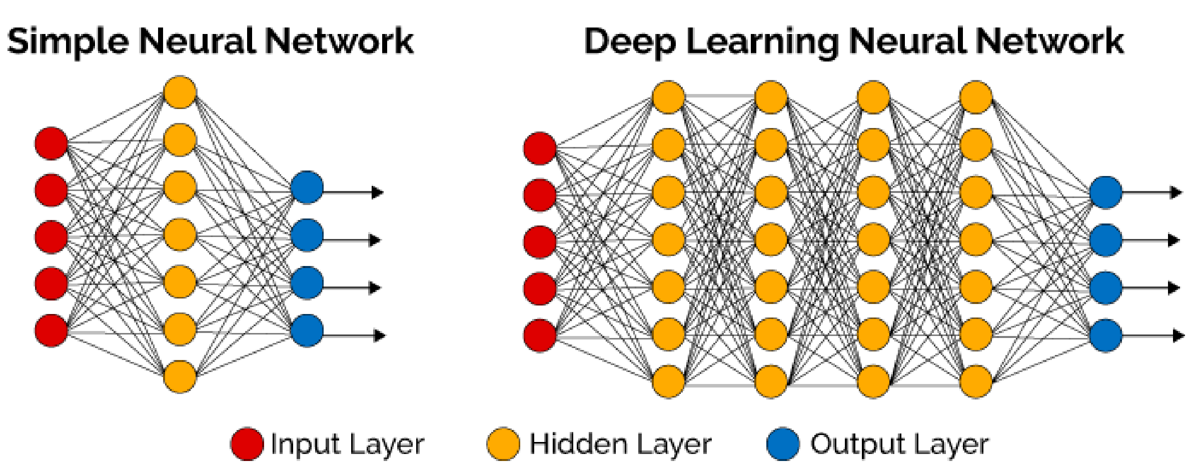

Fig. 2 Deep neural network for feature classification and extraction by performing nonlinear multiresolution analysis
Source: ibsstore.com.

The fundamental theorem about neural networks is the universal approximation theorem. It says that with reasonable activation, a network containing only one hidden layer can closely approximate any continuous function. This only happens when the network parameters are strictly defined. Note that even though a neural network with one hidden layer can approximate any function, it is highly unscientific for large-scale problems as the number of neurons increases exponentially. In deep neural networks, the width and depth of these networks can be combined for greater precision and large-scale analysis in a non-linear fashion. In deep neural networks, the problem of nonlinearity is one of the first to be solved.

Recognizing that the process from image to features is a function of progress, the corresponding process from features to image is an inverse function. This analogy may seem asymmetric because the neural networks were based on a problem. They are therefore semantic, while data acquisition captures physical interactions. At a higher level, we find that the physics of the reconstruction is the same. Therefore, the next steps should be calculated on a similar basis. Both the backpropagation function and the inverse function should be implemented in the same way. Both processes should be performed thanks to the internal capabilities of neural networks, through forwarding or backward propagation. In computed tomography, we have a issue with the complexity of the problem, which is why we will often have to fight the entanglement of features and the curse of multidimensionality.

Over the past few years deep learning has undoubtedly been successful, but we still know so little about reconstructing projection images using deep neural networks. We often don't fully understand how CNN (Convolution Neural Network) can be improved to achieve effective solutions. From a physics perspective, a neural network behaves as before the same, but at different scales. Each neuron is governed by an activation function that accepts data written in the form of the internal product. This product is a fundamental construction for deep learning. Most of the transformations are calculated using internal products, i.e. projections on the appropriate spaces of the examined object. Cross-correlations are internal products that are used in the feature discovery process. Both projections and back projections are also a product of internal products. The inner product operation is linear. A deep neural network is much more "intelligent" than a tool for solving linear systems. In a deep neural network, linear and non-linear steps can be integrated when performing complex computational tasks. The principle of simplicity is also applicable to information science.

It is worth noting that a large proportion of reconstruction algorithms are designed to solve linear problems. The linear model is accurate, so it is not necessary to change its analytical insight in favor of non-linear feature processing in the deep neural network. Deep imaging is a good technique to fully exploit field expertise, especially when dealing with large amounts of data. This approach cannot be used by iterative Bayesian algorithms that are nonlinear. The reconstruction algorithm should be simple, and this approach is one of the foundations of deep imaging. There is also some level of criticism in deep learning. Images may differ in different classes [6]. Criticism in this area is advisable because we still know little about neural networks, especially in the context of reconstructing tomographic images.

Image denoising using deep neural networks

Many factors in computed tomography will translate into the appearance of noise in the image, including metal implants or a low dose of radiation, which will reduce the legibility of the obtained image. From a mathematical point of view, we know that stationary Poisson noise scales with signal intensity. This means that brighter pixels will have more noise than darker pixels. The effect, however, is more severe in the case of a low signal. Detector noise affects every pixel, regardless of the true signal. In some solutions, it is modeled as an additive Gaussian noise process. The amount of noise can be quantified by comparing the performance of noise reduction algorithms or by assessing the improvement in a certain set of data. The standard approach is to calculate the inner square error (1).

$$MSE(x,s)=\frac{1}{n}\sum_{i=1}^{n}(x_i-s_i)^2 \qquad (1)$$

The difference of squares is averaged over all pixels and an image with a total of n pixels. MSE is suitable for noise comparisons between images but sometimes leads to surprising and unintuitive results when comparing the quality of two different images. Image denoising aims to provide a function f (x, y) = s which takes a noisy image as input and returns an image approximation on the output. Effective noise reduction is possible thanks to two basic elements. First is based on the knowledge of the noise distribution in an image. But how likely is it that solving s will result in a variable x? Second is based on our knowledge of what pure images look like. We can assume that the image will be smooth and possible to limit so that it falls within a certain "smoothness" range of the probability distribution [8].

Deep learning methods do not make clear assumptions about noise modeling. Instead, they teach how to expect specific patterns based on a set of training data. Neural networks learn what such an image should look like for the currently used dataset. Deep neural networks deliver optimal results. In computed tomography, we will deal with detector noise.

Summary

Scientific progress is not constant, as Dr Thomas Kuhn has already recognized. He introduced his philosophical view on scientific progress [7]. Kuhn did not present science as continuous progress but emphasized breakthrough discoveries, each of which leads to the discovery of a new paradigm of thinking and acting. A new paradigm has been added that combines empirical, simplified complexity, theory, and data mining. Currently, it is more often referred to as machine learning with Big Data, thus emphasizing that the driving force is the exploration of large or small data. The fifth paradigm is the so-called brain-computer intelligence that takes learning to the next level. The world is constantly evolving and there are even more groundbreaking ideas ahead of us.

Literature

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