

Convolutional neural network-based approaches to video image analysis

LIN ZHENQUAN

Research Scholar Lincoln University College Malaysia

Abstract

The focus of this research is on providing a foundational understanding of convolutional neural networks for its application, in particular, to the detection of moving objects. Furthermore, the paper details the functioning and interplay of convolutional layers. Manually analysing a

huge dataset of video stills is now the only viable option, but this is time-consuming and requires human expertise. The algorithms included into neural networks allow for autonomous analysis and identification.

Keywords: video analysis, convolutional neural networks, convolutional layers, identification, moving objects.

INTRODUCTION

When it comes to efficient pattern recognition, deep learning technology's convolutional neural networks (CNN) are the way to go. The term "convolutional neural network" describes a kind of network that employs a mathematical technique known as convolution. For those unfamiliar, convolution is a specific kind of linear process. Convolution is used in place of matrix multiplication in at least one layer of convolutional neural networks. Over the last decade, CNNs have seen widespread use for image identification applications. This opens up a wide range of possibilities for developers to use this technology, particularly in fields that involve probabilistic identification and contain a big number of characteristics.

Convolutional neural networks are useful for a number of tasks, including spotting players in live sports broadcasts. With the use of several cameras, sports analysts may collect information about the game and where each player was at any given moment. The analysis that follows may be used for a number of purposes, such as enhancing the transmission of sports footage,

recreating a 3D match so that the viewer can see all the action unfolding on it, and offering interactive material. Additionally, the information gained through CNN work streamlines the collecting of game data to aid coaches in doing tactical analysis and enables you to settle contentious game situations with less room for mistake.

Many researchers are now focusing on the problem of how to properly label things in space. Researchers have looked at several aspects of machine learning [2], including creating identification models [4] and improving the clarity of photographs of moving objects [5]. This both increases the quantity of data collected throughout the match and makes analysing that data more easier. The goal of this research is to summarise previous work on convolutional neural networks applied to moving images. The study yielded sufficient information for us to formulate a broad strategy.

We introduce convolutional neural networks, describe their primary functions, and outline the primary techniques used in this field. This ensures a deeper comprehension of the theoretical aspects of the problem, including how convolution and analysis of the compressed picture are carried out.

Many businesses now base their offerings on cutting-edge deep learning technology: Facebook's automated tagging is performed by use of neural network algorithms. Instagram for search infrastructure, Google to search the user's images, Amazon to propose products, and so on.

One key component of CNN is the use of a large number of alternating convolutional layers. Because each layer addresses a different challenge, the final product of the method is an illustration of a class or classes of probability that are most likely to describe this picture. Moving across the water picture, the filter conducts convolution by multiplying the filter values by the original pixel values. There is a cumulative total of all these multiplicative operations. The final tally is a single digit. The steps are then repeated for each vacant slot (Figure 1). To continue, shift the filter to the right by one, then again by one, and so on.

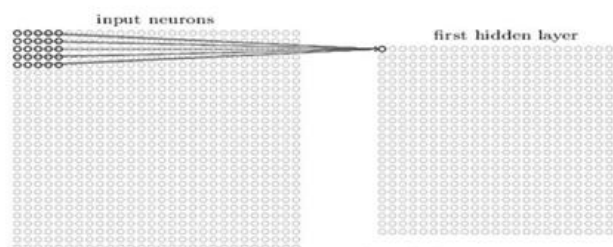


Figure 1. – Visualization of filter convolving around an input volume and producing an activation map [1].

One way to think of a filter is as a unique identifier for a property. Curves, borders, and solid colours are all valid choices for the ID attribute (Figure 2).

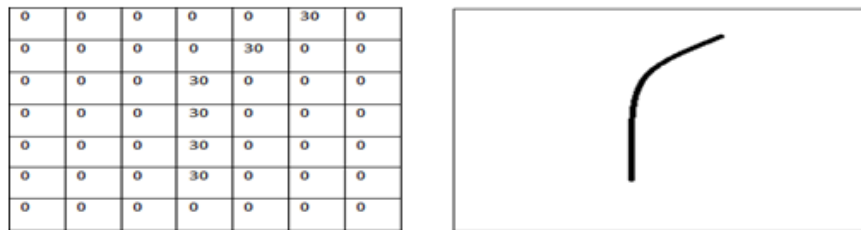


Figure 2. – Pixel representation of filter and visualization of a curve detector filter.

The filter's values are multiplied by the pixel values of the upper-left corner of the input picture when the filter is placed there.

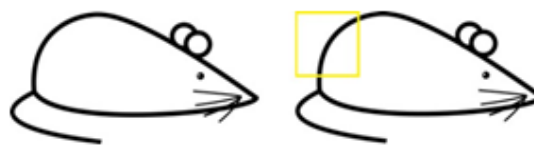


Figure 3- Original image and visualization of the filter on the image [3].

When all the multiplied values are combined together, a huge number is produced if the input picture has a form that is fairly comparable to the curve that this filter depicts (Figure 4). As a result of this high likelihood, the filter has been triggered to look for a curve in the picture. Adjustments have been made to relocate the filter (Figure 5).

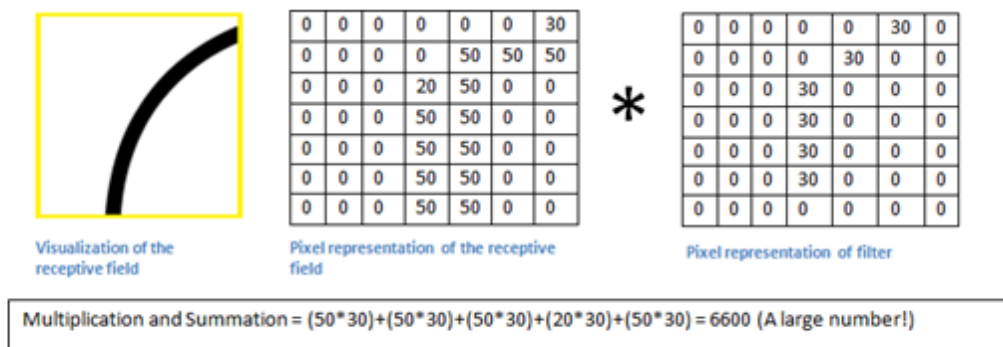


Figure 4. – The result of the filter in the first position [3].

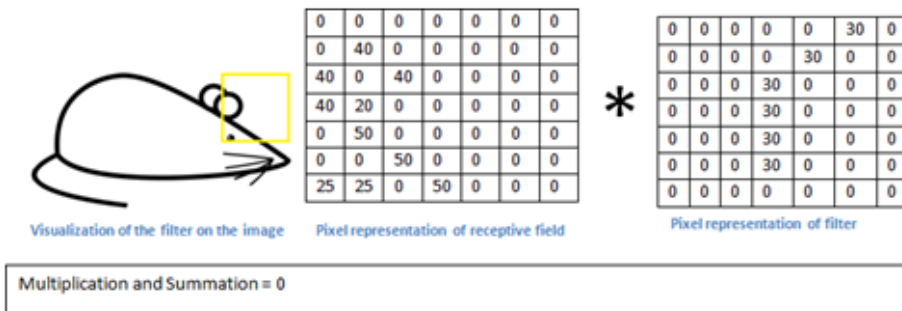


Figure 5. – The result of the filter in the second position [3].

This new number is far lower than the old one. This region of the picture does not have a curve that is comparable to the one the filter is searching for, thus it returns an error.

Tasks requiring the detection of moving objects are particularly well-suited to algorithms based on convolutional neural networks. The following text discusses the outcome of an algorithm that enhances the quality of photographs taken of a huge number of moving objects. It was a team of Chinese researchers in the lab who introduced this approach [5]. The numbers show off three different states for contrasting purposes. In the first place, there are Range Doppler Algorithm (RD)-created data point targets (Range-Doppler algorithm is one of the most popular synthetic aperture radar processing algorithms). Second is the final picture that the algorithm produced. The third option represents the best possible outcome. Information is supplied for a variety of object speeds. The outcomes, as shown in Figures 6 and 7, are for inert items. The outcomes for 12 m/s-moving items are shown in Figures 8 and 9.

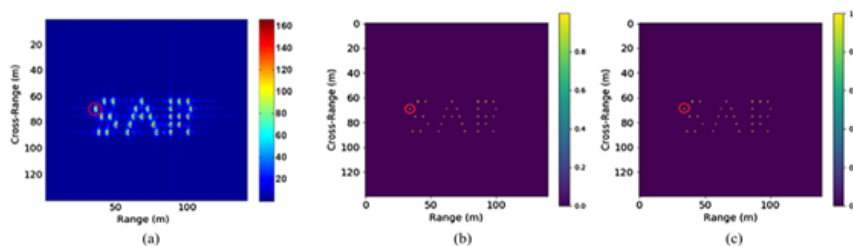


Figure 6. - Imaging results of the stationary point target. (a) RD algorithm. (b) U-net output (c) Ideal scattering point model [5].

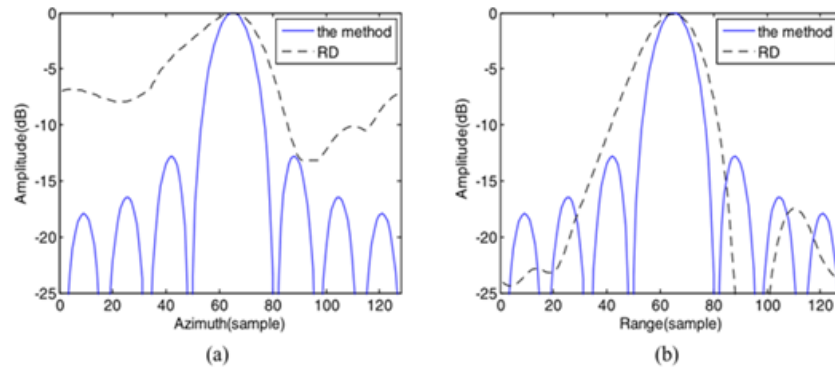


Figure 7- Profile comparison of the scattering point marked by the red circle in Fig. 6. (a) Comparison in azimuth. (b) Comparison in range [5].

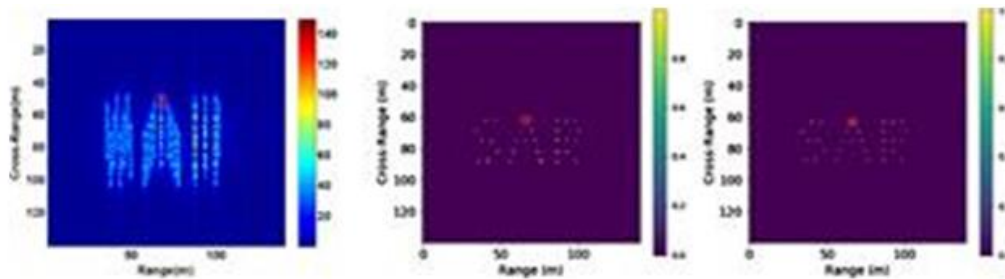


Figure 8. - Imaging results of the moving point target with azimuth velocity of 12 m/s. (a) RD algorithm. (b) U-net output. (c) Ideal scattering point model [5].

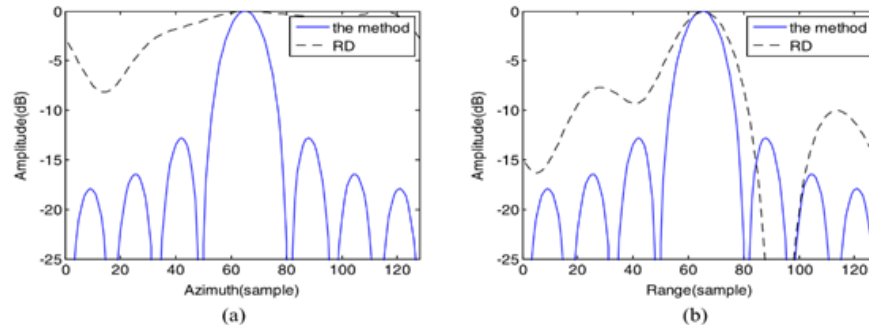


Figure 9. - Profile comparison of the moving point marked by the red circle in Figure 8. (a) Comparison in azimuth. (b) Comparison in range [5].

The photos show that the convolutional neural network-based technique can produce reasonably accurate snapshots of moving objects by filtering out background noise. In addition, the outcome is very near to the ideal indications, whether we're talking about a perfectly still item or a very fast-moving one.

In the study, we define convolutional neural networks. We examine the underlying philosophy of convolution matrices. In this example, we show how to use convolutional layers and analyse the data they produce. We show how to create an algorithm based on convolutional neural networks by using it to analyse a picture of moving objects. The study's findings equip us to go further deeper into the issue and contribute to future studies of its kind.

REFERENCES

1. Adit Deshpande. A Beginner's Guide To Understanding Convolutional Neural Networks - 2020 - Text: electronic URL: [https://adeshpande3.github.io/A-Beginner's- Guide-To-Understanding-Convolutional-Neural-Networks/](https://adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks/) -(Reference date 26.12.2020).
2. Ivet Rafegas, Maria Vanrell, Luis A. Alexandre, Guillem Arias. Understanding Trained CNNs by Indexing Neuron Selectivity// Pattern Recognition Letters/ Text: electronic. – 2019- URL: <https://www.sciencedirect.com/science/article/abs/pii/S0167865519302909> - (Reference date 26.12.2020).
3. Michael Nielsen. Neural Networks и Deep Learning Text: electronic. – 2019 – URL: <http://neuralnetworksanddeeplearning.com/chap1.html> -(Reference date 26.12.2020).
4. RuihengZhang, LingxiangWu, YukunYang, WannengWu, YueqiangChen, MinXu. Multi-camera multi-player tracking with deep player identification in sports video //Pattern Recognition 2020 - Text: electronic. – URL: <https://www.sciencedirect.com/science/article/abs/pii/S0031320320300650> - (Reference date 26.12.2020).
5. Zhi-junLu, QiQin, Hong-yinShi, HaoHuang - SAR moving target imaging based on convolutional neural network. //Digital Signal Processing- Text: electronic. – URL: <https://www.sciencedirect.com/science/article/abs/pii/S1051200420301779> - (Reference date 26.12.2020).