Object tracking with deep neural networks

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Contents

Abstract ii

Abstract (in Finnish) iii

Contents iv

1 Introduction 1

2 Deep Learning 2
2.1 Deep neural networks . . . 2
2.2 Convolutional neural networks . . . 3
2.3 Stacked denoising autoencoders . . . 5

3 Object tracking 6
3.1 Target representation . . . 6
3.2 Datasets . . . 6
3.3 Evaluation . . . 7

4 Deep neural networks in tracking 8
4.1 Trackers using convolutional neural networks . . . 8
4.2 Other approaches . . . 9

5 Conclusions 11

References 12

Abbreviations

CNN Convolutional Neural Network

DNN Deep Neural Network

FCN Fully Convolutional Network

ILSVRC ImageNet Large Scale Visual Recognition Challenge

LSTM Long Short Term Memory

MLP MultiLayer Perceptron

MOT Multiple Object Tracking challenge

NN Neural Network

ReLU Rectified Linear Unit

SDAE Stacked Denoising Autoencoder

VOT Visual Object Tracking challenge

1 Introduction

Object tracking is a large and actively researched sub-area of computer vision. The main task for a tracker is to find and follow the desired subject in a sequence of images. Object tracking is closely related to other image analysis tasks so the implementations also share elements. In the recent years, use of deep neural networks has been researched for object tracking.

Many of the deep networks tailored to tracking tasks are variations of convolutional networks. Another way used to extract features from a frame is a stacked denoising autoencoder [1]. The training of deep neural networks requires a large amount of training data and their development has been made easier by an increase in the size of applicable datasets.

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The goal of this thesis is to study the concepts behind object tracking and deep neural networks. It will present the architectures and principles currently used in deep neural networks tailored to object tracking tasks. The practices and datasets used in training and evaluating such networks are also introduced.

2 Deep Learning

Neural networks are heavily researched for numerous applications and they are loosely based on the way a brain functions. The basic model a Neural Network (NN) consist of inputs, outputs and a connecting layer of neurons. This chapter introduces the basic concepts behind general deep neural networks, convolutional neural networks and stacked denoising autoencoders. 2.1 and 2.2 are based on the book Deep Learning by Goodfellow et. al. [2].

2.1 Deep neural networks

A Deep Neural Network (DNN) is commonly defined as a NN that has a **visible** input and output layer with several **hidden layers** between them. The distinction between visible and hidden layers is important because training of the network only evaluates the output layer's performance. During training, a **learning algorithm** optimizes the individual hidden layers to best approximate the desired output of the whole network.

The input layer takes in the data to be processed, which typically means a vector of color values in the case of object tracking. These are then processed by the hidden layers and finally the output layer produces the target's position in the frame. These models usually come in the form of a **feedforward neural network** or **MultiLayer Perceptron (MLP)**. The name comes from the fact that information flows from the input through computations to the output with no **feedback** connections. Typically this means that connections are only between consecutive layers.

In NNs, each layer consist of several **units** with an activation function and a weight for each of their input connections. The weights of the layer's inputs are commonly represented by a matrix by which the input vector is multiplied as each row represents a unit's input weights. All of the units can be connected to all of the inputs (fig.1) forming a fully connected layer or just some of them (fig.2) utilizing sparse connections. Sparse layers can be implemented by defining unique input vectors for the units. Units in a layer have a common activation function that is fed by the sum of its weighted inputs. The **Rectified Linear Unit (ReLU)** is a commonly used unit type and is defined by the activation function $g(z) = \max\{0, z\}$. It provides a nonlinear transformation while being comparable to linear models in terms of generalizing well and being easy to optimize. A bias-term can also be defined for each unit and a vector containing the layer's biases is summed to the outputs of the activation function before passing the results to the next layer.

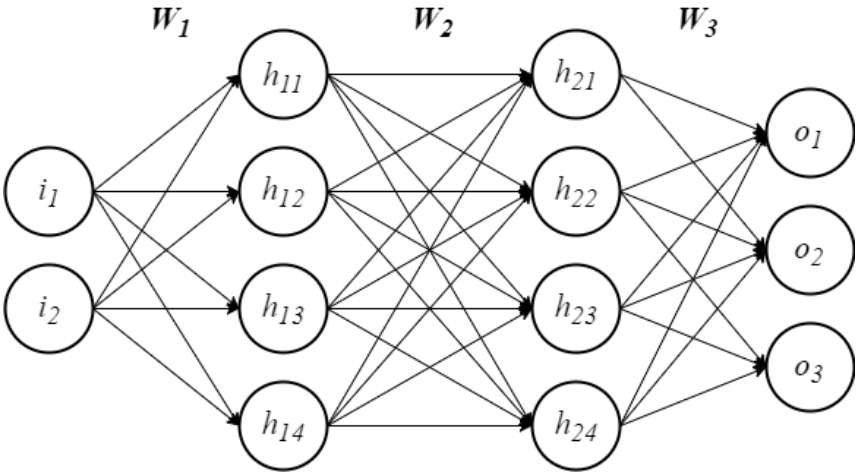


Figure 1: A fully connected network with two inputs i, two hidden layers of four units h and three outputs o. Each set of connections is represented by a weight matrix $\mathbf{W}$ which indicates mapping from one layer to another. Excluding the input, all layers also have an activation function and their units can be assigned individual weights.

Before training, the weights of a MLP are initialized to small random values and biases to zero or small positive values. Then an algorithm called **stochastic gradient descent** is commonly applied alongside a training dataset. The basic procedure is to calculate the error of the netwok's output values compared to the desired ones using a **loss function**. The function's gradient can then be calculated for example by **back-porpagation**, which feeds the errors back through the network to assign a contribution value to each unit. These values are then used to calculate the gradient of the loss function relative to the weights. Each weight is adjusted slightly to the opposite sign to minimize the loss function.

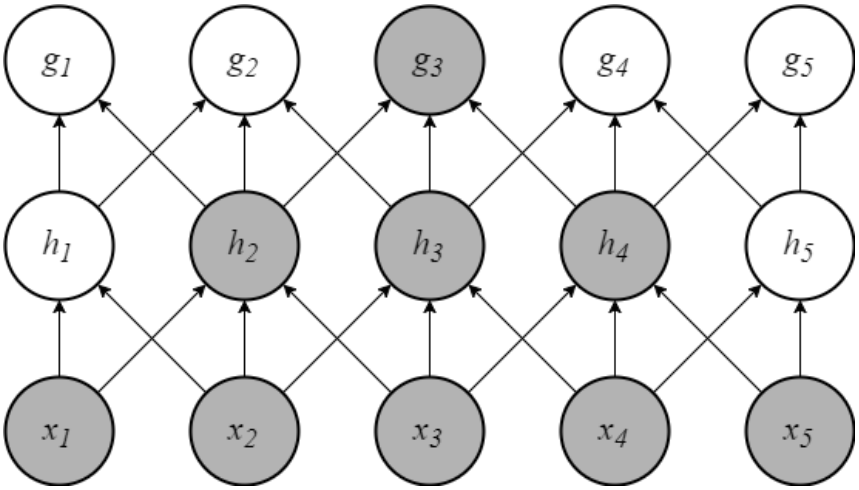
2.2 Convolutional neural networks

"Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers" [2]. Intuitively, convolution can be viewed as a blending of two functions as it is an integral expressing the overlap of two functions as one is moved over the other. A convolution performed on integers is by definition an infinite summation but it can be implemented on a finite number of elements if the functions are considered zero for all values that are not stored. In a Convolutional Neural Network (CNN), a convolution defined by this property is performed on the input data and a kernel in the form of a vector of weights learned in training.

A typical convolutional layer consists of three stages: a convolution stage, detector stage and pooling stage. These operations can be implemented by individual layers. First, the multiplication of the kernel and the input data is performed in positions separated by a stepsize. The result is then fed to a linear activation function. In the detector stage, the results are then run through a non-linear activation, for example a ReLU. Finally, a **pooling function** is used to combine the results of multiple

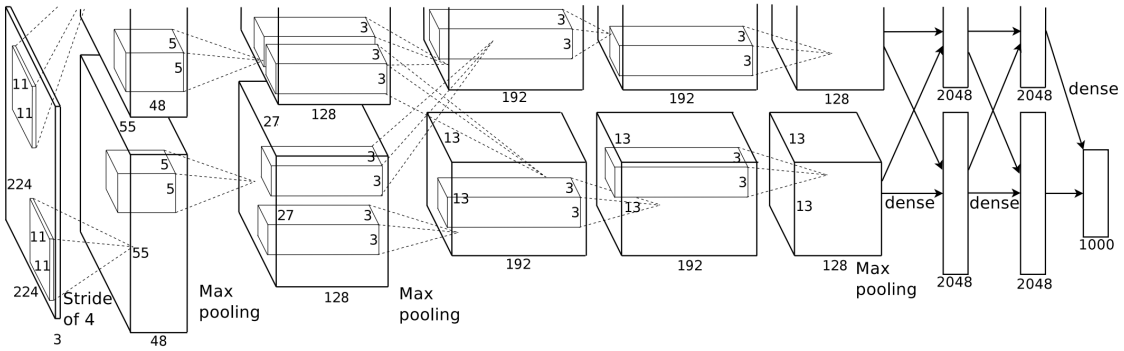
nearby activations as the final output.

The main motivations in using CNNs are sparse interactions, parameter sharing and equivariant interactions. Units in traditional layers are connected to all of the input so an input sized m and output of size n form a computational complexity of $m \times n$. Convolutional layers' units typically only connect to a small portion of the input, which can be a significant decrease in computation: a kernel of size k results in a complexity $k \times n$ and k can be kept several orders of magnitude smaller than m. It is also possible to share the same kernel for all positions in the input to reduce the number of weights stored from $m \times n$ to just k. Parameter sharing in convolution also results in equivariance to translation. It is a useful property in processing 2D data as a shift in the input results in a similar shift in the output. Equivariance to some other transformations is not inherent to convolution so other mechanisms are required for handling them.



Source: Recreated fig. 9.4 from Deep Learing [2]

Figure 2: Stacking convolutions can can provide deeper layers indirect connections to most or all of the input data even though their direct connections are sparse. This forms hierarchies of features that are useful for capturing larger concepts and the effect increases if a strided convolution or pooling is used. [2]



Source: Krizhevsky et. al. page 5. [3]

Figure 3: A branch in the network of Krizhevsky et. al. [3] is a good example of a basic CNN architecture. The first layer uses a 11×11×55 kernel and feeds into layers of increasing depth with the final convolutional layer working with a 3×3×192 kernel. The final layers are fully connected with 4096 neurons and produce the networks output as a vector of probabilities over the 1000 trained subject classes.

2.3 Stacked denoising autoencoders

Autoencoders consist of an encoder, a decoder and a loss function. They first encode the given data to a hidden representation and then reconstruct it while the loss function is used in training. Reconstructing the exact input data is not useful and denoising autoencoders avoid that by learning to encode a corrupted version of the input and decode the result into useful features of the clean input. A stacked denoising autoencoder utilizes a sequence of encoders followed by matching decoders trained this way. Corrupted input data is only used to train the individual layers to find useful features as a trained Stacked Denoising Autoencoder (SDAE) works on clean input. [4]

Comment by author: motivation for using sdaes?

3 Object tracking

Object tracking in video sequences has been researched for decades using different approaches for defining the target and adapting to changes in its shape or orientation. The situations most likely to cause tracking failure have also been identified.

Comment by author:
Define the problem in more depth

3.1 Target representation

Early influential works in the field have used target models including subspaces [5] and representing the target as a curve [6]. Modern tracking methods can be roughly divided to generative and discriminative, but combinations of them have also been proposed.

Comment by author:
cite a combination

Generative methods search the frame for the best matches to a template of an appearance model of the subject. Template methods based on pixel intensity and color histograms perform well with no drastic changes in object appearance and non-cluttered backgrounds. Appearance models learned from training can be less affected by appearance variations and adaptive schemes provide added flexibility, while sparse models handle occlusion and image noise better. [7]

Comment by author:
add citations

Discriminative methods consider tracking as a binary classification problem. They take the background also into account to separate the target from it. Used approaches include refining the initial guess with a support vector machine [8] or utilizing a relevance vector machine [9].

During tracking, the appearance of the target may change for example due to changes in orientation. Some trackers adapt the tracking model online to be robust against such changes, but care must be taken in designing the update algorithm as it could result to drift.

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Give some examples, cite

3.2 Datasets

The datasets used for training are equally important as the actual network design

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citation

. Research on networks working with image data has been made easier by larger sets of both hand-labeled sets and ones obtained by simple keyword searches from online image services. These kinds of sets can be used to pre-train useful target features to tracking networks.

VOC was a yearly competition for object recognition and VOC 2012 [10] is the last challenge in the series. The datasets of the challenges are still used for pre-training features for detection stages in tracking networks. There are

four major subsets of hand-labeled VOC data: classification, segmentation action classification, person layout. Classification datasets consist of images annotated with the objects contained and bounding boxes for the objects drawn in the image itself while image segmentation sets provide additional mask images of the objects and classes in each shot. Action classification sets contain descriptions and bounding boxes of actions the subjects are performing and person layout sets contain bounding boxes for the subjects head, hands and feet.

Comment by author:
image examples of the datasets, descriptions to annotations

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [11] is another recognition challenge running since 2010. The most recent dataset consists of subsets of object localization, object detection and object detection from video. The last subset is especially beneficial object tracking tasks as it provides data for training on actual tracking data. The other two sets are also substantially larger than the respective VOC sets as their labeling has been crowd sourced.

There has also been an increase in resources solely devoted to tracking data with the TB-100 -set [12] being a good example. It contains a hundred tracking sequences with reference positions for the target on each frame. Because some of the targets are similar or less challenging, a subset of 50 sequences considered challenging is also provided as TB-50. [13]

The datasets used for the Visual Object Tracking challenge (VOT) [14] can also be used for training networks. The competition is run yearly with updated evaluation sets which can be used for training as training data for a network but the challenge itself prohibits training on tracking datasets for participants.

There is also the yearly Multiple Object Tracking challenge (MOT) [15] for testing multiple object trackers but its unique sequences can also be used to train single object trackers one object at a time.

3.3 Evaluation

Evaluation of proposed trackers is a vital part of the research. It also limits the use of annotated tracking sequences in training as training and evaluation should be done on different data.

Comment by author:
present the metrics used in evaluation

The Visual Tracker Benchmark [12] is a commonly used resource for comparing performance to other trackers. It consists of the TB-datasets, a code library containing implementations of 31 publicly available trackers and ready benchmark results for the included trackers. The code library is implemented using MATLAB and all included trackers have been modified to use unified input and output formats. A Python-based testing suite is also in development. The original benchmark was compiled in 2015 so doesn't include more recent trackers in the suite. The VOT [14] and MOT [15] challenges also publish both the yearly challenge suite and results, which can used to compare new networks against the participants.

4 Deep neural networks in tracking

Trackers based on deep learning have been researched because of DNNs' ability to capture hierarchies of features from raw data with minimal earlier domain specific knowledge. They provide greater versatility compared to traditional trackers that are based on hand-crafted sets of features. This chapter discusses effective trackers that consist of DNNs.

4.1 Trackers using convolutional neural networks

Multilayered CNNs are currently common as feature extractors, but an early implementation of a CNN-based tracker [16] pre-dates the work of Krizhevsky et. al. [3] that sparked the current research on DNNs for classification tasks. Fan et. al. [16] proposed a shift-variant architecture utilizing the previous tracking result each frame. They recognized crowded scenes containing multiple objects similar to the target to be especially challenging as false positives could result in drift from the intended target. A reference position from the previous frame was used to provide additional information for locating the target in the current one. They also considered the shift-invariancy of conventional CNNs to present its own challenges. Shift-invariancy means that the position of an object does not affect the network's output, which is beneficial for classification tasks as it is desirable to recognize the objects in an image regardless of their position. However, a tracker is expected to identify the location of the target, which motivated the adoption of a shift-variant architecture. [16]

The tracker Fan et. al. [16] presented had separate input layers for extracting feature maps from the current and previous frame. These were then downsampled together before splitting the rest of the convolutions into two branches to obtain both global and local structures of features. Global structures were extracted via a series of convolutions, while local structures were discovered by sampling the branching output with a single layer of small kernels. The network's final layer took the outputs of both branches and produced the final probability map based on them. Training was performed on a set of 20,000 images obtained from surveilance videos and it was supervised as the probabality map resulting from a pair of frames was compared to a target map. Online traking was done on a fixed model to avoid the drift adaptive models can induce. The proposed tracker perfomed especially when the target's position or the view changed as the tracker was trained to track humans specifically. [16] Only being able to track a single class of targets is a major limitation, but more recent trackers have used similar approaches in conjuction with training on multiple different object classes.

[17] Learns branching and domain specific fully connected layers and the online tracking substitutes them with a single new layer that is fine-tuned online with the shared layers. Both long- and short-term updates are utilized to provide both robust and adaptive tracking.

[18] No pre-training as the network learns features online. Model is updated if training loss is above a certain threshold.

[19] Combines a pre-trained feature descriptor CNN and a SVM that creates a

saliency map from the extracted features. This map is used as a filter to extract the position of the target in each frame.

[20] Applies a siamese architecture of two convolutional networks to object tracking. A candidate image is compared to an exempla image and is scored based on their similarities.

[21] Combines an efficient feature extractor (YOLO) to spatial and temporal constraints. The network's layers are first pre-trained with a traditional CNN for general feature learning. YOLO is then adopted as the detection module and the Long Short Term Memory (LSTM) is added before training it as part of the whole network. The LSTM is provide robust access to long-range context and is fed with the output of the detection stage converted to a 32x32 heatmap linked with the learned visual features.

[22] Uses the conv4-3 and conv5-3 layers of the VGG network for selecting feature maps that are fed to two different networks: a general network to capture category information and a specific network to discriminate the target from the background. Both networks output heatmaps which are used for final detection. The general network's result is used by default while the specific network is used to determine the target location if a distracter is detected in the background. Both networks are initialized on the first frame, but only the specific network is updated online to avoid noise.

[23] Instead of using just the final output of a sequence of convolutional layers, the proposed algorithm uses multiple layers to find the target's position. This is done by going through the outputs coarse-to-fine to regularize the search for the maximum value in the finer response maps. All the layers' correlation filter numerator and denominator are also updated each frame to get a robust and computationally lighter approximation of minimizing output error.

[24] Views the traditionally fully connected layers at the end of a CNN based tracking network as convolutional layers and uses upscaling with skip connections to previous layers. This Fully Convolutional Network (FCN) is computationally lighter than a sliding window based network as it only requires a single feedforward [connection?]. The network was pre-trained on the VOC2012 dataset to learn features for targets of 20 categories in the dataset. The tracker is only able to detect objects in those categories. It also only allows single object tracking but the target can be identified in the first probability map if the sequence contains multiple targets to permit multi-object scenarios and increase accuracy in single-object tracking. (However, the method is currently not efficient enough for tracking in real time.)

4.2 Other approaches

Not all trackers based on a DNN use CNNs for feature extraction. Wang and Yeung [1] proposed DLT, a tracker consisting of a pre-trained SDAE and an additional classification layer. The SDAE was trained on the Tiny Images dataset and its encoder part was used with a sigmoid classification layer for online tracking.

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THIS IS USES CONVOLUTIONAL LAYERS FOR FEATURES, might be too shallow

The ideas behind DLT were developed further by Wang et. al. [25]. They observed that DLT couldn't obtain deep features with temporal invariance due to training on unrelated images. Another remark was that DLT doesn't have an integrated objective function to adapt the encoder to a target as the weights are only updated if the target appearance seems to have changed during tracking. The new feature learning method was integrated into an existing tracking system called ASLSA [26], which originally used raw pixel valus as its representations.

The two layer feature model learned features capable of handling complicated motion transformations based on the work of Zou et. al. [27]. It was trained on auxiliary video sequences and the goal was to learn features invariant between two frames, which results high-level features robust to non-linear motion patterns. These generic features didn't include appearance information of specific target objects so a domain adaptation module was added to both layers in order to to readjust them according to a specific target. [25]

Evaluation on some challenging sequences showed that the tracker Wang et. al. [25] proposed was able to track targets that underwent non-rigid object deformation and in- or out-of-plane rotations. It was also observed to perform better than the baseline trackers and beat DLT in 5 of the 8 sequences tested. However, the tracker was implemented as a single-threaded CPU program it only reached 0.6 fps in comparison to the 15 fps of the GPU implementation of DLT [1].

[28] Uses a SDAE fine-tuned with SURF features gotten from matching the current frame's to the first one's.

[29] Tackles the issue of motion blur as it is common in actual applications of object tracking. Deblurring the images online is not computationally viable so the work proposes a blur-invariant object tracker. It uses a deep hierarchial appearance model pre-trained with unlabeled data that is blurred with varying kernel sizes to make the model more robust.

5 Conclusions

Summarize the current state of object tracking with DNNs with possibly some insight to future developments.

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