Object tracking with deep neural networks

Santeri Salmijärvi

School of Electrical Engineering

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Thesis supervisor:

D.Sc. (Tech) Pekka Forsman

Thesis advisor:

M.Sc. (Tech) Mikko Vihlman

Aalto University
School of Electrical Engineering

AALTO UNIVERSITY
SCHOOL OF ELECTRICAL ENGINEERING

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Contents

Abbreviations

CNN Convolutional Neural Network

DNN Deep Neural Network

FCN Fully Convolutional Network

LSTM Long Short Term Memory

MLP MultiLayer Perceptron

NN Neural Network

ReLU Rectified Linear Unit

SDAE Stacked Denoising Autoencoder

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 applicaple 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 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. The first two sub-sections 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 Neural Network (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.

In NNs, each layer consist of several **units** with a weight and activation function. A bias-term can also be defined for each unit. The weights of a layer are commonly represented by a matrix by which the input-vector is multiplied. Units in a layer also have a common activation function, which is fed by the sum of its weighted inputs in addition to the possible bias, and the result is output to the next layer alongside the layers other units' outputs. A commonly used unit type is the **Rectified Linear Unit (ReLU)**, which 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.

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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 networks

A Convolutional Neural Network (CNN) is simply a NN that uses convolution instead of general matrix multiplication in at least one of its layers. The main benefits of convolution in NNs are that it's dramatically more efficient in terms of memory requirements, it reduces the amount of computation needed and it makes it possible to work with variable input sizes.

A typical convolutional layer consists of three stages: a convolution stage, detector stage and pooling stage. These can be implemented by individual layers. First, a **kernel** is applied to the input data in positions separated by a stepsize. This means that a linear activation function is fed by the matrix product of the input location and the kernel's weight matrix. 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 outputs as the final output.

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Convolutional layers enable indirect connections to all or most of the input data deeper in the network even when individual layers' connections are very sparse.

2.3 Stacked denoising autoencoders

A Stacked Denoising Autoencoder (SDAE) is a modification of the classic autoencoders. Denoising autoencoders are trained to encode a corrupted version of the input to a hidden representation and decode that to useful features of the clean input. A stacked denoising autoencoder is simply a sequence of denoising autoencoders trained this way. Corrupted input is only used to train the individual layers to find useful features so a trained SDAE works on clean input. [3]

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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.

3.1 Target representation

Early influential works in the field have used target models including subspaces [4] and representing the target as a curve [5]. Modern tracking methods can be roughly divided to generative and discriminative, but combinations of them have also been proposed.

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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. [6]

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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 [7] or utilizing a relevance vector machine [8].

3.2 Model update

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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3.3 Challenges

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Present challenging situations for trackers, motivation for development of better methods.

4 Data sets and evaluation

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Overview of the data sets used for training and analysis. Methods used for comparing performance.

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

There has also been an increase in resources devoted to tracking data with the TR-100 -set [9] introduced in 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 TR-50. [10]

5 Deep neural networks in tracking

(Overview of task from DNN-point of view, strengths and weaknesses compared to more traditional solutions.)

An early implementation of a CNN-based tracker [11] pre-dates the work of Krizhevsky et. al. [12]. It takes modifies the architecture used for detection to make the network less affected by sifts in the objects position in the frame. Shift-invariancy is a non-desirable quality in tracking while using previous positions as a as it might result to mixups with objects similar to the target. [11]

[13] Learns generic features from video sequences with tracked objects and focuses on features robust to complex motion patterns. An adaptation module integrates the target's shape and texture to the pre-trained features. This is done using the first 20 frames of the online tracking sequence as training data.

[14] 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.

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

[16] 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.

[17] 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.

[18] 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.

[19] 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.)

[20] 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.

[21] 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.

[22] 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.

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

6 Conclusions

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

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