Chapter 1

Related work

1.1 Action Recognition

First approaches for action classification consisted of two steps a) compute complex handcrafted features from raw video frames such as SIFT, HOG, ORB features and b) train a classifier based on those features. These approaches made the choise of features a signifact factor for network's performance. That's because different action classes may appear dramatically different in terms of their appearance and motion patterns. Another problem was that most of those approaches make assumptions about the circumstances under which the video was taken due to problems such as cluttered background, camera viewpoint variations etc. A review of the techniques, used until 2011, is presented in Aggarwal and Ryoo 2011.

Recent results in deep architectures and especially in image classification motivated researchers to train CNN networks for the task of action recognition. The first significant attempt was made by Karpathy et al. 2014. They design their architecture based on the best-scoring CNN in the ImageNet competition. they explore several methods for fusion of spatio-temporal features using 2D operations mostly and 3D convolution only in slow fusion. Simonyan and Zisserman 2014 used a 2 CNNs, one for spatial information and one for optical flow and combined them using late fusion. They show that extacting spatial context from videos and motion context from optical flow can improve significantly action recognition accuracy. Feichtenhofer, Pinz, and Zisserman 2016 extend this approach by using early fusion at the end of convolutional layers, instead of late fusion which takes places at the last layer of the network. On top that, they used a second network for temporal context which they fuse with the other network using late fusion. Futhermore, Wang et al. 2016 based their method on Simonyan and Zisserman 2014, too. They deal with the problem of capturing long-range temporal context and training their network given limited training samples. Their approach, which they named Temporal Segment Network (TSN), seperates the input video in K segments and a short snippet from each segment is chosen for analysis. Then they fuse the extracted spatio-temporal context, making, eventually, their prediction.

Some other methods included a RNN or LSTM network for classification like Donahue et al. 2014, Ng et al. 2015 and Ma et al. 2017. **Pending... description**

Additionally, Tran et al. 2014 explored 3D Convolutional Networks (Ji, Yang, and Yu 2013) and introduced C3D network which has 3D convolutional layers with kernels $3 \times 3 \times 3$. This network is able to model appearence and motion context simultaneously using 3D convolutions and it can be used as a feature extractor, too. Combining Two-stream architecture and 3D Convolutions, Carreira and Zisserman 2017 proposed I3D network. On top of that, the authors emphasize in the advantages of transfer learning for the task of action recognition by repeating 2D pre-trained weights in the 3rd dimension. Hara, Kataoka, and Satoh 2017 proposed a 3D ResNet Network for action recognition based on Residual Networks (ResNet) (He et al. 2015) and explore the effectiveness of ResNet with 3D Convolutional kernels. Diba et al. 2017 **Pending ...** Tran et al. 2017 experiment with several residual network architectures using combinations of 2D and 3D convolutional layer. Their purpose is to show that a 2D spatial convolution followed by a 1D temporal convolution achieves state of the art classification performance, naming this type of convolution layer as R(2+1)D. A more detailed presentation for Action Recognition techniques used until 2018 is included in Kong and Fu 2018.

1.2 Action Localization

As mentioned before, Action Localization can be seen as an extention of the object detection problem. Instead of outputing 2D bounding boxes in a single image, the goal of action localization systems is to output action tubes which are sequences of bounding boxes that contain an performed action. So, there are several approaches including an object-detector network for single frame action proposal and a classifier.

The introduction of R-CNN (Girshick et al. 2013) achieve significant improvement in the performance of Object Detection Networks. This architecture, firstly, proposes regions in the image which are likely to contain an object and then it classifies them using a SVM classifier. Inspired by this architecture, Gkioxari and Malik 2014 design a 2-stream RCNN network in order to generate action proposals for each frame, one stream for frame level and one for optical flow. Then they connect them using the viterbi connection algorithm. Weinzaepfel, Harchaoui, and Schmid 2015 extend this approach, by performing frame-level proposals and using a tracker for connecting those proposals using both spatial and optical flow features. Also their method performs temporal localization using a sliding window over the tracked tubes.

Peng and Schmid 2016 and Saha et al. 2016 use Faster R-CNN (Ren et al. 2015) instead of RCNN for frame-level proposals, using RPN for both RGB and optical flow images. After getting spatial and motion proposals,Peng and

Schmid 2016 fuse them exploring and from each proposed ROI, generate 4 ROIs in order to focus in specific body parts of the actor. After that, they connect the proposal using Viterbi algorithm for each class and perform temporal localization by using a sliding window, with multiple temporal scales and stride using a maximum subarray method. From the other hand, Saha et al. 2016 perform, too, frame-level classification. After that, their method performs fusion based on a combination between the actioness scores of the appearence and motion based proposals and their overlap score. Finally, temporal localization takes place using dynamic programming.

On top of that, Singh et al. 2017 and Kalogeiton et al. 2017 design their networks based on the Single Shot Multibox Detector Liu et al. 2015). Singh et al. 2017 created an online real-time spatio-temporal network. In order their network to execute real-time, Singh et al. 2017 propose a novel and efficient algorithm by adding boxes in tubes in every frame if they overlap more than a threshold, or alternatively, terminate the action tube if for k-frames no box was added. Kalogeiton et al. 2017 designed a two-stream network, which they called ACT-detector, and introduced anchor cuboids. For K frames, for both networks, Kalogeiton et al. 2017 extract spatial features in frame-level, then they stack these features. Finally, using cuboid anchors, the network extracts tubelets, that is a sequence of boxes, with their corresponding classification scores and regression targets. For linking the tubelets, Kalogeiton et al. 2017 follow about the same steps as Singh et al. 2017 did. For temporal localization, they use a temporal smoothing approach.

Most recently, YOLO Network (Redmon et al. 2015) became the inspiration for Hu et al. 2019 and El-Nouby and Taylor 2018. In Hu et al. 2019, concepts of progression and progress rate were introduced. Except from proposing bounding boxes in frame level, they use YOLO together with a RNN classifier for extracting temporal information for the proposals. Based on this information, they create action tubes, seperated into classes. Some other approaches include pose estimation like Luvizon, Picard, and Tabia 2018, and. In Luvizon, Picard, and Tabia 2018 uses **pending description...**.

Most of aforementioned networks use per-frame spatial proposals and extract their temporal infomation by calculating optical flow. On the other hand, Hou, Chen, and Shah 2017 design an architecture which icludes proposal in video segment level, which they called Tube CNN (T-CNN). Video segment level means that the whole video is seperated into equal length video clips, and using a C3D for extracting features, it returns spatio-temporal proposals. After getting proposals, Hou, Chen, and Shah 2017 link the tube proposals by an algorithm based on tubes' actioness score and overlap. Finally, classification operation is performed for the linked video proposals.

1.3 Our implementation

We propose a network similar to Hou, Chen, and Shah 2017. Our architecture is consisted by the following basic elements:

- One 3D Convolutional Network, which is used for feature extraction. In our implementaion we use a 3D Resnet network which is taken from Hara, Kataoka, and Satoh 2018 and it is based on ResNet CNNs for Image Classification He et al. 2015.
- Tube Proposal Network for proposing action tubes (based on the idea presented in Hou, Chen, and Shah 2017).
- A classifier for classifying video tubes.

Pending ... more commentary and a figure

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