Recurrent Fully Convolutional Networks for Video Segmentation

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Abstract

Image segmentation is an important step in most visual tasks. While convolutional neural networks have shown to perform well on single image segmentation, to our knowledge, no study has been been done on leveraging recurrent gated architectures for video segmentation. Accordingly, we propose a novel method for online segmentation of video sequences that incorporates temporal data. The network is built from fully convolutional element and recurrent unit that works on a sliding window over the temporal data. We use convolutional gated recurrent unit that preserves the spatial information and reduces the parameters learned. Our method has the advantage that it can work in an online fashion instead of operating over the whole input batch of video frames. The network is tested on the change detection dataset, and proved to have 5.5% improvement in F-measure over a plain fully convolutional network for per frame segmentation. It was also shown to have improvement of 1.4% for the F-measure compared to our baseline network that we call FCN 12s.

1 Introduction

Recent trend, in convolutional neural networks has dramatically changed the landscape in computer vision. The first task that has been vastly improved with this trend is object classification [12][19][21]. An even harder task that has seen great progress is semantic segmentation, which provides per pixel labelling as introduced in [14][26]. In [14] the introduction of fully convolutional network that yields coarse map, is followed by upsampling within the network to get dense predictions. This method enabled an end-to-end training for the task of semantic segmentation of images. However one missing element in this recent trend is the fact that real-world is not a set of still images. A large portion of the information that we infer from the environment is from motion. For example, in an activity recognition task, difference between walking and standing is only profound if you consider a sequence of images.

The conventional Convolutional Neural Networks (CNN) are not designed to include temporal changes and attempts to forge it to do so, were not particularly fruitful so far. The simplest way to include temporal information in CNN is to just concatenate multiple frames and feed it to the input. Small variations of this method is used for context classification on one million youtube videos[11]. Surprisingly, they could not improve on single frame prediction by much which can indicate the inefficiency of this simple approach. [15] creates a network which learns transformations between frames of long video sequences. In [22] convolutional restricted Boltzman machine is introduced and it can learn optical flow like feature from input image sequence. Another proposed method [17] uses Recurrent Neural Networks (RNN) which has shown its power in tasks such as speech recognition. The article introduces a combination of CNN and RNN for video segmentation however as

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they mention the RNN architecture is sensitive to initialization and training it is difficult due to the vanishing gradient problem. Their design also does not allow usage of pre-trained network that can greatly help generalization.

In the field of recurrent networks and recurrent gated units several architectures have been proposed that solved the main bottleneck of recurrent networks namely vanishing or exploding gradients. In [6] Long Short Term Memory (LSTM) was presented, and since then was used for various applications like generating sequences for text [7], dense image captioning [10] and video captioning [6]. Another architecture recently suggested is Gated Recurrent Unit (GRU) [4]. It was shown in [5] that LSTM and GRU outperform other traditional recurrent architectures, and that GRU showed similar performance to LSTM but with reduced number of parameters. One bottleneck with these previous architectures, is that they only work with variable length sequences as input and output. Thus they're incapable of handling data where spatial information is relevant like images or feature maps. In [18] convolution LSTM was introduced that can maintain the spatial information, it was used on weather radar data for precipitation now-casting. Another work in [1] that used convolutional GRU which worked for learning spatio-temporal features from videos. In their work experiments on video captioning and human action recognition was conducted.

The usage of fully convolutional networks (FCN) combined with recurrent gated units can solve many of the pitfalls of the previous approaches. In this paper we present: (1) A novel architecture that can incorporate temporal data directly into FCN for video segmentation. We have chosen the Recurrent Neural Network as the foundation of our structure since it is shown to be effective in learning temporal dynamics. (2) An end-to-end training method for online video segmentation, that does not need to process data offline. To our knowledge this is the first work that presents recurrent fully convolutional network using convolutional gated unit to yield pixelwise labelling.

The paper is structured as follows. In Section 2 we will discuss the background, then the proposed method will be presented in details in section 3. That is followed by the experiments section and discussion of the results in section 4. Finally, section 5 concludes the paper and presents potential future directions.

2 Background

This section will review FCN and RNN which will be repeatedly referred to through the article.

2.1 Fully Convolutional Networks (FCN)

In convolutional neural networks that are used for classification, the last fully connected layers are responsible for the classification part. But with pixel-wise labelling there is a need for dense predictions instead of just a single class output. In [13] the idea of using a fully convolutional neural network that is trained pixel by pixel for semantic segmentation is presented. It is shown that it surpasses the state of the art in semantic segmentation on PASCAL VOC, NYUDv2 and SIFT Flow datasets. The FCN method is briefly discussed in what follows.

FCN architecture is based on VGG [19] architecture due to its success in classification tasks, so it was desirable to adapt them to segmentation. However, due to the fully connected layers that these networks have, they can only accept fixed size input and produce a classification label. To overcome this problem, it is possible to convert the fully connected layer into a convolutional layer. Then this network can yield coarse maps pixel wise prediction instead of one classification output.

In order to have dense predictions from this coarse map, there is a need for upsampling which can be simple bi-linear interpolation. But in [13] a new layer that applies upsampling within the network was presented. It is efficient to learn the upsampling weights within the network using back-propagation. The filters of the deconvolution layer act as basis to reconstruct the input image. Another idea for upsampling is to stitch together output maps from shifted version of the input. But It was mentioned in [13] that using upsampling with deconvolution is more effective. In [16] the idea of having a full deconvolution network with both deconvolution layers and unpooling layers is presented.

The initial version of the FCN that is with 32 stride, limits the details that is presented in the pixel-wise labels. To handle this problem instead of using the sequential topology for a network, a directed
acyclic graph was used. Where it sums the output map from two paths. The first map from the 32 stride after being upsampled twice. The second map is from the previous pooling layer that is 16 stride output map followed by 1x1 convolution to have predictions. This network is called the 16s version, and the 8s version is similar but combining with even finer output maps.

The FCN architecture has been tried in different applications. In [9] it is used for object localization. Also in [24] a modified architecture was used for visual object tracking. Finally for semantic segmentation in [16] a full deconvolution network is presented with stacked deconvolution layers.

2.2 Recurrent Neural Networks

Recurrent Neural Network [23] is designed to incorporate temporal information into a neural network framework. These networks are capable of learning complex dynamics by utilizing a hidden unit in each recurrent cell. This unit works like a dynamic memory that can be changed based on the state that the unit is in. Accordingly, process of each unit yields to two outcome. First, an output is computed from the current input and the hidden units values (the networks memory). Secondly, the network updates its memory based on, again, current input and hidden units value. The simplest recurrent unit can be modeled as follows:

\begin{align}
    h_t &= \theta \phi(h_{t-1}) + \theta x_t \tag{1a} \\
    y_t &= \theta_y \phi(h_t) \tag{1b}
\end{align}

where \( h \) is the hidden layer, \( x \) is the input layer and \( y \) is the output layer and \( \phi \) is the activation function.

Recurrent networks have proven successful in many task in speech recognition and text understanding [20]. Unrestricted data flow between units causes problems with vanishing and exploding gradients [3]. During the back propagation through recursive units, the derivative of each node is dependant of all the nodes which came earlier. This is shown in equations 2,3, and 4 where \( E \) is the loss of the layer. To compute \( \frac{\partial h_t}{\partial h_k} \) a series of multiplication from \( k = 1 \) to \( k = t - 1 \) is required. Assume that \( \dot{\phi} \) is bounded by \( \alpha \) then

\[
| \frac{\partial E}{\partial h_k} | < \alpha^{t-k}
\]

A solution to this problem is to use a gated structure. These gates can control back propagation flow between each node. Long-Short Term Memory [8] is the first such proposed architecture and is still popular. A more recent architecture is Gated Recurrent Unit [4] which has simpler cells and has competent performance [5].

2.2.1 Long Short Term Memory (LSTM)

As mentioned, LSTM uses a gated structure where each gate controls the flow of a particular signal. Each LSTM node has three gates that are the input, output and forget gate each with learnable weights. These gates can learn the optimal way to remember useful information from previous
states and decide the current state.

\[ i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \]  
\[ f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \]  
\[ o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \]  
\[ g_t = \sigma(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \]  
\[ c_t = f_t \odot c_{t-1} + i_t \odot g_t \]  
\[ h_t = o_t \odot \phi(c_t) \]  

**2.2.2 Gated Recurrent Unit (GRU)**

The Gated Recurrent Unit, similar to LSTM, utilizes a gated structure for flow-control. However, it has a simpler architecture which makes it both faster and less memory consuming. The model is shown in Figure 1 and described below.

\[ z_t = \sigma(W_{hz}h_{t-1} + W_{xz}x_t + b_z) \]  
\[ r_t = \sigma(W_{hr}h_{t-1} + W_{xr}x_t + b_r) \]  
\[ \hat{h}_t = \Phi(W_h(r_t \odot h_{t-1}) + W_x x_t + b) \]  
\[ h_t = (1 - z_t) \odot h_{t-1} + z \odot \hat{h}_t \]  

GRU does not have direct control over memory content exposure while LSTM has it by having an output gate. These two are also different in the way that they update nodes memory. LSTM updates its hidden state by summation over flow after input gate and forget gate. GRU however, assumes a correlation between how much to keep from the current state and how much to get from previous the state and it models this with the \( z \) gate.

**2.2.3 Convolutional Gated Recurrent Unit (Conv-GRU)**

Conventional recurrent units are capable of processing temporal data however, their architecture are not suitable for working on images/feature maps for two reasons. 1) weights matrix size, 2) ignoring spatial connectivity. Assume a case where a recurrent unit is placed after a feature map with the spatial size of \( h \times w \) and have number of channels \( c \). After flattening, it will turn in to a \( c \times h \times w \) long matrix. Therefore, weights of the recurrent unit will be of size \( c \times (h \times w) \) which is power four of spatial dimension. These matrices for weights can only be maintained for small feature maps. Even if the computation was not an issue, one can ask that if such large number of parameters is even necessary for working on feature maps that are derived from images. Since each pixel of image, usually, do not carry its own independent value but instead are closely correlated with nearby pixels. Therefore, having individual set of weights for each pixel, is not only a waste of memory but it also makes the learning task much more difficult.

In this new design, similar to regular convolutional layer, weights are three dimensional and convolve with the inputs instead of dot product. Accordingly, the cell’s model, in case of a GRU architecture, will turn into equations where the dot products are replaced with convolutions. In this design, weights matrices are of size \( k_h \times k_w \times c \times f \) where \( k_h, k_w, c \) and \( f \) are kernel’s height, kernel’s width, number of input channels, and number of filters, respectively. In Figure 1 the operations applied on the input and the previous step will all be convolutions instead. Since we can assume spatial connectivity in feature maps, kernel size can be very small compared to feature...
map’s spatial size. Therefore, this architecture is much less computationally heavy and weights are easier to learn due to smaller search space.

\[
z_t = \sigma(W_{hz} * h_{t-1} + W_{xz} * x_t + b_z) \tag{7a}
\]

\[
r_t = \sigma(W_{hr} * h_{t-1} + W_{xr} * x_t + b_r) \tag{7b}
\]

\[
\hat{h}_t = \Phi(W_h * (r_t \odot h_{t-1}) + W_z * x_t + b) \tag{7c}
\]

\[
h_t = (1 - z_t) \odot h_{t-1} + z \odot \hat{h}_t \tag{7d}
\]

3 Method

3.1 Method Overview

At an abstract level, we use a recurrent fully convolutional network (RFCN) that utilizes the temporal information. Instead of the batch/offline version which needs the whole video as input, we work in an online fashion. This is done by using a sliding window over the frames. Then each window is propagated through the RFCN and yields the output. The output can be segmentation (or more specifically semantic segmentation) or it could be captions for the video or other applications that will benefit from temporal data. The recurrence part is created by using a recurrent gated unit that takes as input feature maps and can output another map if it is a segmentation task or a sequence if used for captioning.

The general architecture used has a fully convolutional network combined with Recurrent unit (RU). The recurrent unit denotes either using LSTM, GRU or Conv-GRU. As shown in Figure 2, a temporal window over the frames of the input video sequence is used as input to our network. Then these group of frames in the temporal window are feed forwarded through the FCN that will output a heat-map per frame. This heat-map is further forwarded into the recurrent part.

![Figure 2: Overview Proposed Method Recurrent FCN](image)

Different architectures under this general design are explored for different datasets. Those architecture are:

- Recurrent Fully Convolutional Lenet (RFC-Lenet)
- Recurrent Fully Convolutional 12 strided (RFC-12s)
- Recurrent Fully Convolutional VGG (RFC-VGG)

3.2 Recurrent Fully Convolutional Lenet (RFC-Lenet)

First architecture was using a lenet network converted to fully convolutional to segment characters. Then combining that with RU after the deconvolution layer of the previous network. In Figure 3,
the architecture is presented. The output from the deconvolution is a 2D map of dense predictions that’s then flattened into 1D vector as input to the recurrent unit. The recurrent unit takes as input the frames, and outputs the segmentation of the last frame. It is then compared with the labels in a logistic loss function.

Figure 3: RFC-Lenet Architecture, F: filter size, S: stride, P: padding, and D: number of channels

3.3 Recurrent Fully Convolutional 12 strided (RFC-12s)

Second architecture is to use the RU before the deconvolution layer and learn on the coarse output map from the last convolution layer. The network has two pooling layers and the first convolution layer has a stride of 3, that is the reason we picked 12 for the stride in the deconvolution. Then the deconvolution is applied on the output of RU. This proved to be useful with larger datasets that had image with higher resolution, that will lead to larger parameters needed in RU. So using these units on the coarse map was faster to compute and had smaller number of parameters. In Figure 4 the new architecture that we propose to use is presented. The RU is having the coarse map as its input and outputs the coarse predictions of last frame processed. Then deconvolution of this coarse map is used to get the dense predictions.

Figure 4: RFC-12s Architecture, F: filter size, S: stride, P: padding, and D: number of channels

3.4 Recurrent Fully Convolutional VGG (RFC-VGG)

Last architecture is based on VGG-F [19] network, where the network is casted to a fully convolutional one by replacing the fully connected layers with convolutional layers. Hence the last pooling layer is dropped from VGG-F and one of the fully connected layers are dropped as well. Then a convolutional gated recurrent unit is used followed by deconvolution for up-sampling. The architecture is shown in Figure 5 and again a logistic loss function is used for training.

4 Experiments

This section presents our experiments and results. First we talk about different datasets that we used, then we discuss our training methods and hyper parameters. Finally, quantitative and qualitative results are shown.
4.1 Datasets

In this project two datasets are used. Moving MNIST and change detection dataset.

4.1.1 Moving MNIST

This dataset is synthesized from original MNIST by moving the characters in random but consistent directions. The labels for segmentation is generated by thresholding input images after translation. We consider each translated image as a new frame. Therefore we can have arbitrary length sequence of images for testing.

4.1.2 Change Detection Dataset

This dataset is used to test our proposed method on real data. It provides realistic, diverse set of videos with pixel-wise labeling of moving objects. The dataset includes both indoor and outdoor scenes. It focuses on moving object segmentation and therefore the labels are indicating any moving objects\(^6\). In the motion detection we were looking for videos that have similar moving objects, e.g.

![Two examples in the change detection datasets. In the top image we have both people and luggage (in the center) moving so both of them markd as true in the ground truth. In the second image, the only moving objects are people cars or humans so that there would be semantic correspondences among sequences. Therefore, we chose six videos from the change detection benchmark that mostly have moving pedestrians.](image)

4.2 Implementation

To our knowledge there is no library that accommodates our architecture. Therefore, we built our own library on top of theano\(^2\) to create arbitrary networks that has both CNN and recursive modules. The key features of our library is enumerated below:

1. Supports network with temporal operation for images. The architecture can be any arbitrary conventional CNN, a recursion layer. The network supports any length input.
2. Three gated architecture, LSTM, GRU, and Conv-GRU is available for the recursion layer.
3. Three optimization methods. SGD, RMSProp and ADAM.

Figure 5: RFC-VGG-F Architecture, F:filter size, S:stride, P: padding, and D: number of channels
4. Deconvolution layer and skip architecture to support segmentation with FCN.

4.3 Results

The main experiments are conducted using Adadelta [25] for optimization that practically gave much faster convergence than standard stochastic gradient descent. The logistic loss function is used and the maximum number of epochs used for the training is 500. The evaluation metrics used are precision, recall, and F-measure shown in equations 8 and 9 where tp, fp, fn denote true positives, false positives and false negatives respectively. The experiments are divided in two sets, one is conducted on synthetic data from MNIST dataset. The other is on real data from change detection benchmark. The first set of experiments is on the synthesized MNIST data, three different architectures are compared against each other:

- A Fully Convolutional Lenet (FC-Lenet) that has deconvolution with stride 4 that is trained on original mnist data and tested on the synthesized one.
- Gated Recurrent Unit only applied on flattened vectors of the input image sequences (LSTM and GRU).
- RFC-Lenet architecture that is presented in section 3.2, and it has the recurrent unit as GRU after deconvolution.

\[
\text{precision} = \frac{tp}{tp + fp}, \quad \text{recall} = \frac{tp}{tp + fn} 
\]

\[
F - \text{measure} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} 
\]

Table 1 shows the results that was obtained on all networks. The results of RFC-Lenet with GRU is better than FC-Lenet with 2% improvement. But segmentation of MNIST characters is an easy task as it ends up to learning thresholding. So it is not enough to use for the evaluation of the RFCN. Also note that GRU gave much better results than LSTM, so for the rest of these experiments GRU will be used for the recurrent unit.

Table 1: Precision, Recall, and F-measure on FC-Lenet, LSTM, GRU, and RFC-Lenet tested on synthesized MNIST dataset

|         | Precision | Recall | F-measure |
|---------|-----------|--------|-----------|
| FC-Lenet| 0.868     | 0.922  | 0.894     |
| LSTM    | 0.941     | 0.786  | 0.856     |
| GRU     | 0.955     | 0.877  | 0.914     |
| RFC-Lenet| 0.96    | 0.877  | 0.916     |

The second set of experiments is conducted on real data from the motion detection benchmark. The sequences that were used throughout the experiments are: Pedestrians, PETS2006, Badminton, CopyMachine, Office, and Sofa. The stopping criteria for the training is either early stopping criteria to prevent overfitting or that it reaches the maximum number of epochs which is 500. Initially some experiments were conducted on pedestrians with 80% for training and 20% testing, that is run on networks below.

- The Fully Convolutional Lenet that has deconvolution with stride 4, denoted as FC-Lenet.
- The Fully Convolutional VGG-F that has deconvolution with stride 8, denoted as FC-VGG. Note that this network takes as input the original images of 240*360, while it received the labels downsampled twice as 120*180. Also the reason for using stride of 8 for the deconvolution is because of having two pooling layers and the initial convolution layer has a stride of 4, while the labels are downsampled already by 2. Note also that the initial 5 convolutional layers are not finetuned, their learning rate adjustments are set to 0 to avoid overfitting the data.
- The pre-training of conv-GRU on the coarse map from FC-VGG.
• The recurrent version of the fully convolutional VGG-F denoted as RFC-VGG, that uses conv-GRU. This was trained in an end-to-end fashion while the FC part was initialized from the weights learned in FC-VGG experiment, and the GRU weights are initialized from the pretraining of GRU experiment. The sliding window used for this experiment is 3 frames.

The results are shown in Table 2, the results of FC-Lenet is better than FC-VGG because of the fact that FC-Lenet has a smaller stride thus the learned coarse map has finer resolution than the one from FC-VGG. It also overfit the data more than FC-VGG that has the initial convolutional layers pretrained on Imagenet. In Figure 7 the final output of this network, and the ground-truth is shown. The results also clearly show that the GRU pre-training on the coarse map output from FC-VGG enhanced the F-measure by 4.2%. While the complete end-to-end training of the RFC-VGG, achieved 5.5% improvement on the fully convolutional counter part. This shows the potential of utilizing temporal information in videos, and how it can enhance the result on fully convolutional counter part.

Table 2: Precision, Recall, and F-measure on FC-Lenet, FC-VGG, pretraining of GRU on FC-VGG coarse map, and RFC-VGG

|            | Precision | Recall | F-measure |
|------------|-----------|--------|-----------|
| FC-Lenet   | 0.931     | 0.919  | **0.924** |
| FC-VGG     | 0.620     | 0.584  | 0.602     |
| GRU pretrained | 0.686   | 0.607  | 0.644     |
| RFC-VGG    | 0.663     | 0.652  | **0.657** |

Then a set of experiments were conducted on all six sequences using the following architectures. Throughout these experiments the training constitute 70% of the sequences, 20% for the validation, and 10% for the test:

• A new architecture that we propose in section 3.2 and denoted as FCN-12s.
• The pretraining of conv-GRU on the coarse map output from FCN-12s.
• The recurrent counter part of the FCN-12s network denoted as RFC-12s, that uses conv-GRU. This one is trained in an end-to-end fashion, where the initial convolutional layers are initialized from FCN-12s experiment, and the GRU is initialized from the pretraining of GRU experiment. The sliding window used in the experiment is 3 frames.

Table 3 shows the results of these experiments, where the RFCN network had a 1.4% improvement over FCN.

Table 3: Precision, Recall, and F-measure on architectures FCN-12s, GRU pretraining on coarse map from FCN-12s, RFC-12s on six sequences from motion detection benchmark for both validation, test data.

|            | Precision | Recall | F-measure |
|------------|-----------|--------|-----------|
| FCN-12s    | 0.827     | 0.585  | **0.685** |
| GRU Pretrained | 0.835   | 0.587  | 0.69     |
| RFC-12s    | 0.797     | 0.623  | **0.7**   |

5 Conclusion and Future Work

In this paper we presented a novel approach in incorporating temporal information for video segmentation. This approach utilizes recurrent units on top of fully convolutional network as a mean to include previously seen frames on deciding the segmentation for the current frame. The paper also introduces convolutional recurrent units (conv-gru in particular) that considers spatial connectivity in the feature maps therefore learn and apply convolutional filters in the recurrent unit. We tested the method on both synthesized and real data for the segmentation task. In both cases we showed that simply having the recurrent layer after either coarse output map or probability map can improve the performance of the segmentation. The proposed architecture can process arbitrary
length videos which makes it suitable for both batch and online scenarios.

For the future work we plan to apply the conv-gru layer on the feature maps instead of coarse output map to improve the results even more. We also want to test this architecture in other visual tasks that can benefit from incorporating temporal data such as activity recognition or video captioning. Another potential future direction is to extend the work for semantic video segmentation.

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