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STFCN: Spatio-Temporal FCN
for Semantic Video Segmentation

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Abstract. This paper presents a novel method to involve both spatial and temporal features for semantic segmentation of street scenes. Current work on *convolutional neural networks* (CNNs) has shown that CNNs provide advanced spatial features supporting a very good performance of solutions for the semantic segmentation task. We investigate how involving temporal features also has a good effect on segmenting video data. We propose a module based on a *long short-term memory* (LSTM) architecture of a recurrent neural network for interpreting the temporal characteristics of video frames over time. Our system takes as input frames of a video and produces a correspondingly-sized output; for segmenting the video our method combines the use of three components: First, the regional spatial features of frames are extracted using a CNN; then, using LSTM the temporal features are added; finally, by deconvolving the spatio-temporal features we produce pixel-wise predictions. Our key insight is to build *spatio-temporal convolutional networks* (spatio-temporal CNNs) that have an end-to-end architecture for semantic video segmentation. We adapted fully some known convolutional network architectures (such as FCN-AlexNet and FCN-VGG16), and dilated convolution into our spatio-temporal CNNs. Our spatio-temporal CNNs achieve state-of-the-art semantic segmentation, as demonstrated for the Camvid and NYUDv2 datasets.

1 Introduction

Semantic segmentation of video data is a fundamental task for scene understanding. For many computer vision applications, semantic segmentation is considered as being (just) a pre-processing task. Consequently, the performance of semantic segmentation has a direct effect on subsequent computer vision solutions which depend on it. Self-driving cars is one of the areas in technology that has received much attention recently. These cars can detect surroundings using advanced driver assistance systems (ADAS) that consist of many different systems such as radar, GPS, computer vision, and in-car networking to bring safety to driving and roads. One of the main processes for the computer vision part of these systems can be identified as being semantic segmentation of all objects in surroundings to transmit accurate and complete information to the ADAS system such that the system can make the best decision to avoid accidents.

Segmentation is typically approached as a classification problem. First, using a set of labeled video frames, the characteristics of all segments (classes) are learned. These characteristics are used for labeling the pixels of test frames [1,51]. Recently, deep learning methods, especially CNNs, ensured state-of-the-art performance in different areas of computer vision, such as in image classification [26], object detection [14], or activity recognition [40].

We consider the application of advanced features, extracted by using CNNs, for semantic video segmentation. Semantic segmentation methods use both given image data at selected locations as well as a semantic context. A set of pixels is usually predicted as defining one class (or even one segment) if connected, and also referring to one particular semantic interpretation.

Previous methods for video segmentation have efficiently exploited CNNs, but they did not use temporal features; of course, temporal features can be useful for interpreting a video semantically. For example, the authors of [1,51] represented and interpreted video frames using a deep learning method, but the main disadvantage of their methods is that they consider those frames as being independent from each other. Neglecting the time dimension in video data basically means that the given raw data are down-sampled without using fully given information. Using temporal features can help the system to distinguishing, for example, between two objects of different classes having the same spatial features but showing differences in the time feature dimension.

Consequently, we propose a method which uses a similar paradigm for extracting spatial features (as in the cited papers), but which differs by also using temporal features (i.e. features of a continues sequences of frames). We propose to identify components which can be embedded "on top" of spatially extracted features maps in individual frames. Such a component can be seen as being equipped with a set of memory cells which save the assigned regions in previous frames. This allows us that relations between regions, available in previous frames, can be used to define temporal features. We process the current video frame by using the spatio-temporal output features of our processing modules.

Similar to other segmentation methods, we use then some fully convolutional layers to perform regional semantic classification. In our method, these fully convolutional layers perform spatio-temporal classifications. Finally, we use a deconvolution procedure for mapping (i.e. scaling) the obtained predictions into the original carrier (i.e. the image grid) of the given frames for having a pixel-wise prediction. See Fig. 1.

CNN-based methods usually combine two components, where one is for describing and inferring a class of different regions of a video frame as a feature map, and another one for performing an up-sampling of the labeled feature maps to the size of the given video frames. An advantage of our method is that we can adjust and embed our proposed module into the end of the first component (before inferring the labels) of current CNN-based methods as an end-to-end network. We show that the proposed changes in the network lead to an improvement in the performance of state-of-the-art methods, such as, FCN-8 [32] and dilated convolution [51].
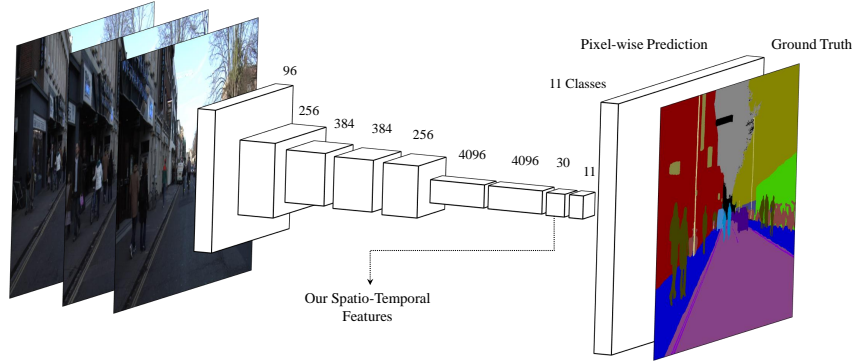
Fig. 1. A spatio-temporal fully convolutional Alexnet architecture, later also to be discussed in Section 4.1

The main contributions of this paper are as follows:

– The proposed method can be easily adapted for enhancing already published state-of-the art methods for improving their performance.
– We propose an end-to-end network for semantic video segmentation in respect to both spatial and temporal features.
– We propose a module for transforming traditional, fully convolutional networks into spatio-temporal CNNs.
– We outperformed state-of-the art methods on two standard benchmarks.

The rest of this paper is organized as follows. Top-ranked related work on semantic video segmentation is reviewed in Section 2. Section 3 introduces the proposed method. The performance of our method is shown in Section 4. Section 5 concludes the paper.

2   Related Work

There is a wide range of approaches that have been published so far for video segmentation. Some of them have advantages over others. These approaches can be categorized based on the kind of data that they operate on, the method that is used to classify the segments, and the kind of segmentation that they can produce.

Some approaches focus on binary classes such as foreground and background segmentation [2,4]. This field includes also some work that has a focus on anomaly detection [37] since authors use a single-class classification scheme and constructed an outlier detection method for all other categories. Some other approaches concentrate on multi-class segmentation [6,29,30,45].

Recently created video datasets provide typically image data in RGB format. Correspondingly, there is no recent research on gray-scale semantic video seg-

mentation; the use of RGB data is common standard, see [12,23,29,30,48]. There are also some segmentation approaches that use RGB-D datasets [17,18,33].

Feature selection is a challenging step in every machine learning approach. The system's accuracy is very much related to the set of features that are chosen for learning and model creation. Different methods have been proposed for the segmentation-related feature extraction phase.

2.1   Feature Extraction

We recall briefly some common local or global feature extraction methods in the semantic segmentation field. These feature extraction methods are commonly used after having super-voxels extracted from video frames [30].

Pixel color features are features used in almost every semantic segmentation system [12,23,29,30,33]. Those includes three channel values for RGB or HSV images, and also values obtained by histogram equalization methods. The *histogram of oriented gradients* (HOG) defines a set of features combining at sets of pixels approximated gradient values for partial derivatives in x or y direction[23,29]. Some approaches also used other histogram definitions such as the hue color histogram or a texton histogram [48].

Further appearance-based features are defined as across-boundary appearance features, texture features, or spatio-temporal appearance features; see [12,23,29,30]. Some approaches that use RGB-D datasets, also include 3-dimensional (3D) positions or 3D optical flow features [18,33]. Recently, some approaches are published that use CNNs for feature extraction; using pre-trained models for feature representation is common in [1,17,49].

After collecting a set of features for learning, a model must be chosen for training a classifier for segmentation. Several methods have been provided already for this purpose, and we recall a few.

2.2   Segmentation Methods

Some researches wanted to propose a (very) general image segmentation approach. For this reason, they concentrated on using unsupervised segmentation. This field includes clustering algorithms such as k-means and mean-shift [31], or graph-based algorithms [12,18,23,47].

A *random decision forest* (RDF) can be used for defining another segmentation method that is a kind of a classifier composed of multiple classifiers which are trained and enhanced by using randomness extensively [16,36]. The *support vector machine* (SVM) [43] or a *Markov random field* (MRF) [38,46] are further methods used for segmentation but not as popular as the *conditional random field* (CRF) that is in widespread use in recent work[5,29,35].

Neural networks are a very popular method for image segmentation, especially with the recent success of using convolutional neural network in the semantic segmentation field. Like for many other vision tasks, neural networks have become very useful [1,14,17,20,32,49].

Fully convolutional networks (FCNs) are one of the topics that interest researchers recently. An FCN is based on the idea of extending a *convolutional network* (ConvNet) for arbitrary-sized inputs [32]. On the way of its development, it has been used for 1-dimensional (1D) and 2-dimensional (2D) inputs [34,44], and for solving various tasks such as image restoration, sliding window detection, depth estimation, boundary prediction, or semantic segmentation. In recent years, many approaches use ConvNets as feature extractor [1,17,49]. Some approaches turn ConvNets into FCNs by discarding the final classifier layer, and convert all fully connected layers into convolutions. By this change, authors use a front-end module for solving their vision tasks [1,14,17,20,32,49].

Recently, a new convolutional network module has been introduced by Yu and Fisher [51] that is especially designed for dense prediction. It uses dilated convolutions for multi-scale contextual information aggregation, and achieves some enhancements in semantic segmentation compared to previous methods. Kundu and Abhijit [27] optimized the mapping of pixels into a Euclidean feature space; they achieve even better results for semantic segmentation than [51] by using a graphical CRF model.

Many approaches that have been introduced in this field have not yet used temporal features, especially in the field of deep CNNs [12,18,23,29,30,48]. These approaches cannot be identified as being end-to-end methods, which points to an essential disadvantage when applying these approaches. Some approaches use deep CNNs [17,27] by introducing an end-to-end architecture for also using spatio-temporal features for semantic labeling. However, none of them can change the size of time windows dynamically.

Long short-term memory (LSTM) is a memory cell module that was introduced by [13,19]. It has many advantages such as the ability to support very large time windows, the ability to change time windows dynamically, the ability to handle noise, distributed representations, continuous values, and so forth. We propose for the first time an approach that uses a deep CNN network with LSTM modules as an end-to-end trainable architecture for semantic video segmentation and labeling.

3   The Proposed Method

3.1   Overall scheme

We have four key steps in our method as shown in Fig. 2. We feed the frame I_t (i.e. the tth frame of a video), into a FCN network. This network down-samples the input images and describes a frame I_t, defined on an image grid Ω of size $W \times H$, as a features set $S_t^{1..m}$ in m different maps. The input is I_t and the output of the latest layer (i.e. of lowest resolution) of the FCN is $S_t^{1..m}$ of size $W' \times H'$, where $W' \ll W$ and $H' \ll H$. As a result, frame I_t is represented as a feature set $\{S_t^{1..m}\}$. Every point (i,j), with $1 \leq i \leq W'$ and $1 \leq j \leq H'$, in $S_t^{1..m}$ is a descriptor of size m for a region (receptive field) in I_t.

We put our *spatio-temporal module* on top of the final convolutional layer. So, feature set $\{S_t^{1..m}\}$ will be represented as a spatio-temporal feature set of
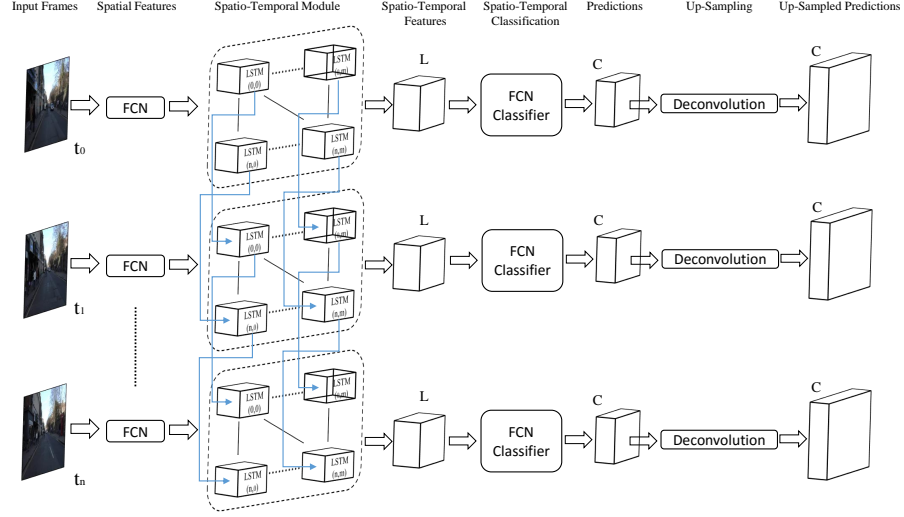
Fig. 2. Overall scheme for our proposed end-to-end network architecture. The LSTMs are used for inferring the relations between spatial features which are extracted from the frames of the video

$\{ST_t^{1..m}\}^{(i,j)}$ by our *spatio-temporal module.* By applying an FCN classifier layer on top of these features, we predict the semantic classes of these regions in the video. Finally, we up-sample these predictions to the size of the I_t frame. In following subsections, the methodologies that have been used in this approach, will be described.

3.2   Fully Convolutional Network

Convolutional neural networks (CNNs) are applied for a large set of vision tasks. Some researchers improve CNNs by changing its basic architecture and introducing new architectures. Recently, fully convolutional networks (FCNs) have been introduced by discarding the final classifier layer, and by converting all fully connected layers into convolutional layers. We follow this principle.

3.3   LSTM

A long short-term memory (LSTM) network is a special kind of *recurrent neural networks* (RNNs) that have been introduced by [19] to solve the vanishing gradient problem and for remembering information over long periods. For an example of a basic RNN and an LSTM cell, see Fig. 3. LSTMs are not confined to fixed-length inputs or outputs, and this advantage makes them powerful for solving sequential problems.
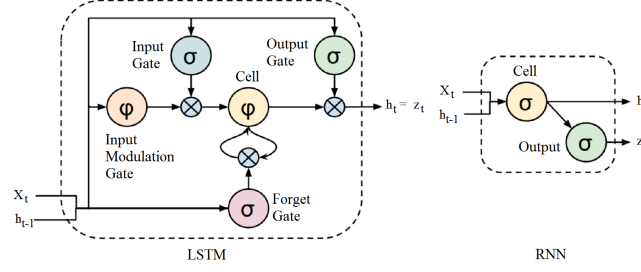
Fig. 3. An example of a basic LSTM cell (*left*) and a basic RNN cell (*right*). Figure follows a drawing in [9]

Each LSTM module consists of a memory cell and a number of input and output gates that control the information flow in a sequence and prevent it from loosing important information in a time series. Assuming S_t as the input of an LSTM module at time t, the cell activation is as formulated in the following equations:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{3}$$

$$g_t = \phi(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{5}$$

$$h_t = o_t \odot \phi(c_t) \tag{6}$$

where σ and ϕ are symbols for a sigmoid and the tanh function, respectively. Symbol $h_t \in R^N$ denotes a hidden state with N units, and $c_t \in R^N$ is the memory cell. By $i_t \in R^N$, $f_t \in R^N$, $o_t \in R^N$, and $g_t \in R^N$ we denote the input gate, forget gate, output gate, and input modulation gate at time t, respectively. Symbol $\odot$ stands for element-wise multiplication.

3.4 Spatio-Temporal Module

In regards to every $W' \times H'$ region of I_t, which is described by an FCN as an Ω grid, an LSTM is embedded (see Section 3.1). Thus we have altogether $W' \times H'$ LSTMs. Element $\{S_t^{1..m}\}^{(i,j)}$ defines a spatial characteristics of a region in the I^t frame. These characteristics are given to LSTM$^{(i,j)}$ for processing; it infers a relation with spatial features of equivalent regions in frames previous to frame I_t. With this "trick", both spatial and temporal features of a frame are considered. (Note that LSTM$^{(i,j)}(\{S_t^{1..m}\}^{(i,j)}) = \{ST_t^{1..m}\}^{(i,j)})$ where S and ST are spatial and spatio-temporal features, respectively).

We embed one LSTM for each region. Equation (7) shows a representation of frame I_t with respect to our suggested spatial and temporal features:

$$\Omega'_t(i,j) = (LSTM^{(i,j)}(\Omega_t(i,j)) \tag{7}$$

where the size of Ω' is equal to that of Ω, and value m specifies a map which assigns spatio-temporal features to every point for describing an equivalent region (i.e. a segment) in I_t. Now, similar to other methods [1,32,51], the labels for points in Ω' are predicted and up-sampled to the frame at the original size. The overall update function can be briefly specified as follows:

$$\Omega'_t(i,j) = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \odot \phi(f_t \odot c_{t-1} + i_t \odot g_t) \qquad (8)$$

Altogether, we introduced an operator layer to several LSTMs for properly representing the temporal features.

This proposed network executes and processes the input frames as an end-to-end network. Figure 2 shows the overall scheme of our method.

3.5   Deconvolution

Interpolation is a common method for mapping outputs into dense pixels. There are several interpolation (or upsampling) algorithms such as bilinear, non-linear, cubic, and so forth. Up-sampling by a factor k can be considered as being a convolution with a fractional input stride of $1/k$. As a result, a convolution operator with input stride of $1/k$ can be applied backward (called deconvolution) with a stride of k [32].

4   Experimental Results

For implementing our *spatio-temporal fully convolutional network* (STFCN) we use the standard Caffe distribution [21] and a modified Caffe library with an LSTM implementation.[1] We merged this LSTM implementations into the Caffe standard distribution and released our modified Caffe distribution to support new FCN layers that have been described in [32]. Our code has been tested on NVIDIA TITAN, and NVIDIA TITAN-X GPUs.[2]

To show the performance of our modified version of FCNs we use their implemented models for two cases, with and without our spatio-temporal module. We tested our STFCN networks on Camvid[3] and NYUDv2[4] datasets. Our evaluation methodology is as in other state-of-the-art semantic segmentation tests, such as in [1,32].

In the following, first we describe the way how we embed our spatio-temporal module into FCNs and dilation convolution networks. Then we describe the metrics used in the evaluation process. After that we report our experiments on CamVid and NYUDv2. Finally, we discuss the performance of our method.

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[1]   Available at `github.com/junhyukoh/caffe-lstm`
[2]   Our modified Caffe distribution and STFCN models are publicly available at `blinded`.
[3]   Available at `mi.eng.cam.ac.uk/research/projects/VideoRec/CamVid/`
[4]   Available at `cs.nyu.edu/~silberman/datasets/nyu_depth_v2.html`

4.1 Embedding the Spatio-Temporal Module in FCN Networks

FCN-8 and FCN-32 [32] are fully convolutional versions of VGG-16 with some modifications to combine features of shallow layers with more precise spatial information with features of deeper layers which have more precise semantic information.

As mentioned in Section 3, it is of benefit to embed the spatio-temporal module on top of the deepest layers. Thus we embed our spatio-temporal module on top of the $fc7$ layer of FCN-8 and FCN-32. The $fc7$ is the deepest fully convolutional layer which has large corresponding receptive fields in the input image. This layer extracts features which represent more semantic information in comparison to shallower layers.

An example of this modification of an FCN-Alexnet is shown in Fig. 1. After embedding our spatio-temporal module in FCN-8 and FCN-32 networks, we call them STFCN-8 and STFCN-32. Our spatio-temporal module consists of LSTMs with 30 hidden nodes and 3 time-steps for the CamVid dataset. We fine-tuned our STFCN networks from pre-trained weights on PASCAL VOC [10] provided by [32]. We used a momentum amount of 0.9, and a learning rate of 10e-5.

4.2 Embedding Our Module in Dilated Convolution Networks

A dilated convolution network is an FCN network which benefits from some modifications such as reducing down-sampling layers and using a context module which uses dilated convolutions. This module brings multi-scale ability to the network [51].

The dilated8 network [51] consists of two modules, front-end and context. The front-end module is based on a VGG-16 network with some modifications. The context layer is connected on top of this module. The $fc7$ layer of the front-end layer provides the main spatial features with 4,096 maps. This network has an input of size $900 \times 1,100$. Because of removing some of its down-sampling layers, the $fc7$ layer has an output of size 66×91 which defines a high dimension for spatio-temporal computations. For overcoming this complexity problem, we down-sampled the output of this layer by a convolution layer to the size of 21×30, and fed it to our spatio-temporal module. Then, the spatio-temporal features are fed to a convolutional layer to decrease their maps to the size of the *final* layer of the front-end module.

After resizing the maps, features are fed to a deconvolution layer to up-sample them to the size of the *final* layer output (66×91). Finally, we fuse them with the front-end *final* layer by an element-wise sum operation over all features.

The fused features are fed to the context module. Let STDilated8 be the modified version of dilated8; see Fig. 4. The spatio-temporal module of STDilated8 consists of 30 hidden nodes of LSTMs with a time-step of 3. For training this network, we fixed the front-end module and fine-tuned the spatio-temporal and context modules with dilation8 pre-trained weights on CamVid. We used a momentum amount of 0.9, and a learning rate of 10e-5.
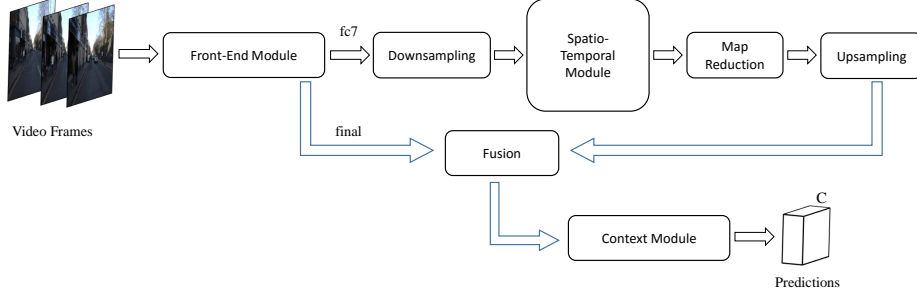
Fig. 4. Our STDilation8 model architecture

For better performance of the spatio-temporal module, we down-sampled the output of the $fc7$ layer of the dilation8 front-end module and fed it to the spatio-temporal module. Then we reduced the feature maps by a fully convolutional layer for a better description of the spatio-temporal features and make them the same size as the final layer of the front-end module. Finally we up-sample and fuse the spatio-temporal features with the final layer output and feed them into the context module.

4.3   Quality Measures for Evaluation

There are already various measures available for evaluating the accuracy of semantic segmentation. We describe most commonly used measures for accuracy evaluation which we have used to evaluate our method.

Mean intersection over union. Mean IU is a segmentation performance measure that quantifies the overlap of two objects by calculating the ratio of the area of intersection to the area of unions [24,48]. This is a popular measure since it penalizes both over-segmentation and under-segmentation separately [38]. It is defined as follows:

$$\frac{1}{n_{cl}} \cdot \sum_i \frac{n_{ii}}{t_i + \sum_j n_{ji} - n_{ii}} \tag{9}$$

where n_{ii} is the number of pixels of class i that is predicted correctly as belonging to class i, t_i is the total number of pixels in class i, and n_{cl} is the number of classes.

4.4   CamVid

The *Cambridge-driving labelled video database* (CamVid) [3] is a collection of videos with object-class semantic labels, complete with meta-data. The database provides ground truth labels that associate each pixel with one of 32 semantic classes. Like in [41], we partitioned the dataset into 367 training images, 100

Table 1. Evaluating FCNs and STFCNs for video semantic segmentation on Camvid (i.e. without or with our spatio-temporal module)

	FCN-32s	STFCN-32s	FCN-8s	STFCN-8s
Mean IU	46.1%	46.9%	49.7%	50.6%

Table 2. Evaluating dilated convolution networks, without or with our module on Camvid

	Dilation8	STDilation8 (90 Frames)
Mean IU	65.3%	65.9%

validation, and 233 test images. Eleven semantic classes are used in the selected images.

For FCN-8, FCN-32, STFCN-8, and STFCN-32, the images are down-sampled to 400×400. For dilation8 and STDilation8, the images are down-sampled to 640×480. As mentioned before, we used time-step 3 for our spatio-temporal module which means that we feed a sequence of 3 frames to our spatio-temporal networks.

The reason for choosing number 3 is that the annotated frames of CamVid have a distance of 30 frames to each other. In fact when we use 3 frames as a sequence, the first and last frame of the sequence have a distance of 90 frames. Using more annotated frames is computationally possible because of the given LSTM abilities, but it is semantically wrong because of the high amount of changes in the frames.

Our results of FCNs and STFCNs tests on CamVid are shown in Table 1. It appears that adding our spatio-temporal module into FCN networks shows an improvement of their performance by close to one percent. Results for dilation8 and STDilation8 tests on CamVid are shown in Table 2. The effect of the spatio-temporal module is here an improvement by 0.8%. Improvements are in both cases not "dramatic" but consistent. Note that reports about improvements in the semantic segmentation area are typically in the sub-one-percent range [27,51,32].

Dilation8 achieves the best results in comparison to other work, and this is due to the power of multi-scale semantic segmentation. STDilation8 achieves even slightly better results because of benefits from temporal features. Detailed results on the CamVid test set are reported in Table 3. Our model outperforms prior state-of-the-art work.

Table 3 shows that some approaches are competitive to related work such as Liu and He [29] with a performance superiority by 0.8 percent compared to SegNet [1]. In contrast, other approaches with a new base architecture achieved a better performance. Since our approach is based on FCN [32] or Dilation8 [51] methodologies, with our introduced spatio-temporal module, performance enhancement is close to one percent on FCN network, and close to 0.8 percent on Dilation8 architecture; both can be considered as a being a noticable enhancement. Dilation + FSO [27] has been published recently based on Dilation8

Table 3. Our STDilation8 improves Dilation8 and outperforms prior work on Camvid

	Building	Tree	Sky	Car	Sign	Road	Pedestrian	Fence	Pole	Sidewalk	bicyclist	mean IU
ALE [28]	73.4	70.2	91.1	64.2	24.4	91.1	29.1	31.0	13.6	72.4	28.6	53.6
SuperParsing [42]	70.4	54.8	83.5	43.3	25.4	83.4	11.6	18.3	5.2	57.4	8.90	42.0
Liu and He [29]	66.8	66.6	90.1	62.9	21.4	85.8	28.0	17.8	8.3	63.5	8.50	47.2
SegNet [1]	68.7	52.0	87.0	58.5	13.4	86.2	25.3	17.9	16.0	60.5	24.8	46.4
STFCN-8	73.5	56.4	90.7	63.3	17.9	90.1	31.4	21.7	18.2	64.9	29.3	50.6
DeepLab-LFOV [7]	81.5	74.6	89.0	82.2	42.3	92.2	48.4	27.2	14.3	75.4	50.1	61.6
Dilation8 [51]	82.6	76.2	89.9	84.0	46.9	92.2	56.3	35.8	23.4	75.3	55.5	65.3
Dilation + FSO [27]	84.0	77.2	91.3	85.6	49.9	92.5	59.1	37.6	16.9	76.0	57.2	66.1
STDilation8	83.4	76.5	90.4	84.6	50.4	92.4	56.7	36.3	22.9	75.7	56.1	65.9

architecture and became state-of-the-art video semantic segmentation method. Our approach differs from FSO in several ways:

- Our approach does not need any pre-processing or feature optimization for result enhancement. In contrast, FSO has used optical flow as a feature set to be used by a CRF model. This is a computational operation which can be considered as a weakness for a semantic segmentation method. Computation efficiency and speed is very crucial in some tasks, such as, online video processing in advanced driver assistance systems. Some researches are ongoing to resolve optical flow computational cost by using convolutional networks [11].
- We used time-step 3 for our spatio-temporal module to use the CamVid dataset annotations as-is without any preprocessing. This simplicity in design and configuration, is one of the strengths of our work.
- Our approach proposes an end-to-end network for semantic video segmentation which consists of spatial and temporal features altogether.
- In our approach we proposed a neural network based module for transforming traditional, fully convolutional networks into spatio-temporal CNNs. It can also be used for other related video processing tasks.

Also, we embedded our spatio-temporal module into FCN-Alexnet and evaluated its performance with and without our spatio-temporal module. Our spatio-temporal module improved its performance on CamVid dataset. Because the basic FCN-Alexnet has a low performance for semantic segmentation as described in [32], so we decided not to include details into this paper.

4.5   NYUDv2

The NYU-Depth V2 data set is comprised of video sequences from a variety of indoor scenes recorded with an RGB-Depth camera [39]. It features 1,449 densely
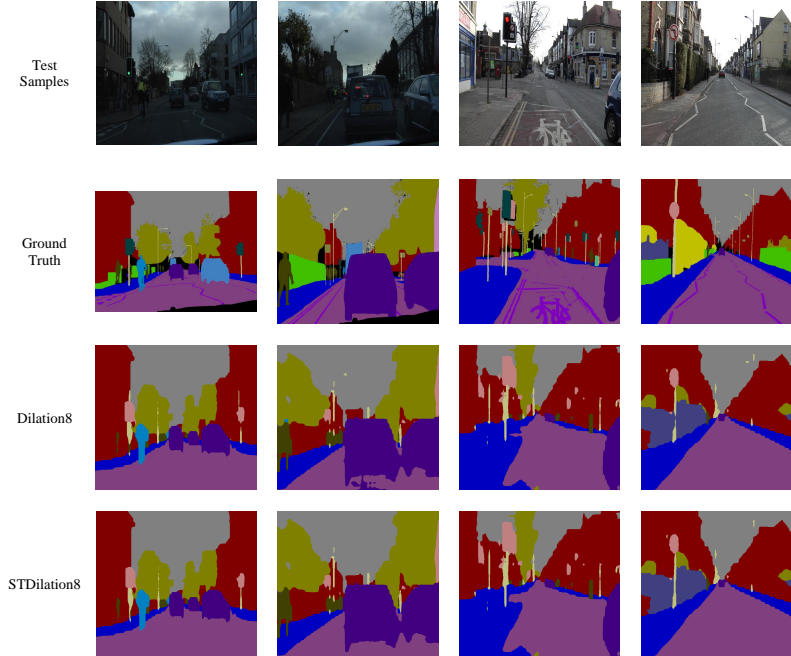
Fig. 5. Outputs on CamVid. *Top to bottom rows:* Test samples, ground truth, Dilation8 [51], and STDilation8

labelled pairs of aligned RGB and depth images, including 464 new scenes taken at three cities, and 407,024 new unlabeled frames.

We selected this dataset to evaluate the effect of multi-modal learning on our spatio-temporal module. Also, we tested our method on two totally different datasets (outdoor vs. indoor) to evaluate its flexibility. One problem of this dataset is that its annotated frames vary in length of sequences per subject or location. Thus, for this dataset, we do not use a constant time step for the spatio-temporal module. We fed sequences of different lengths based on their location. This problem showed its effect on results by decreasing the amount of improvements compared to none-temporal models.

Gupta et al. [16] coalesced NYU-Depth V2 into 40 classes. Similar to [32] we report results on a standard split into 795 training images and 654 test images. We selected our models based on [32] to be able to evaluate an embedding of our spatio-temporal module into their models. We use FCN-32s RGB and FCN-32s RGBD models to embed our spatio-temporal module in the way as explained before. Tests on NYUDv2 data are reported in Table 4.

Results show in this case the enhancement effect of the spatio-temporal module on FCN-32s RGB and FCN-32s RGBD compared to the related networks FCN-32s RGB and FCN-32s RGBD, respectively.

Table 4. Evaluating STFCNs, FCNs, and dilated convolution networks for semantic video segmentation on NYUDv2

Network	Pixel Accuracy	Mean Accuracy	Mean IU
Gupta *et al.* [15]	60.3%	–	28.6%
FCN-32s RGB [32]	60.0%	42.2%	29.2%
FCN-32s RGBD [32]	61.5%	42.4%	30.5%
STFCN-32s RGB	60.9%	42.3%	29.5%
STFCN-32s RGBD	62.1%	42.6%	30.9%

4.6   Discussion

We showed the power of our spatio-temporal module by embedding it into other known spatial, fully convolutional networks. In fact we introduced a spatio-temporal, fully convolutional network for extracting spatio-temporal features from video data and evaluated it based on two semantic segmentation case studies.

Our module benefits from the LSTM characteristics and is able to handle long-short term sequences. In our tests we were only able to use a limited number of video frames as being one sequence because of the limited number of available annotated frames. The method should also be tested on datasets with more extensive sets of annotated frames to check the effect of sequence length on the performance of the system. It is possibly also of value to check the effect of involving unannotated frames into input sequences by using prior or posterior annotated frames in the system.

5   Conclusions

In this paper we proposed a new architecture for spatio-temporal feature extraction from video. We designed and used this architecture for semantic video segmentation. First, a pre-trained CNN model was turned into an FCN model by changing classification layers into fully convolutional layers. In this phase, spatial features from input frames can be used for classification. But, in semantic video segmentation, relationships between frames can provide very useful information and enhance the accuracy of the segmentation program. Therefore, LSTM modules have been used to take advantage of temporal features. This architecture has been proposed as an end-to-end trainable model and can also be used for other vision tasks. Also, it does not need to be a pre-processing or post-processing module only, as we have seen in some other approaches.

We illustrated the performance of our architecture by embedding our spatio-temporal module into some state-of-the-art fully convolutional networks, such as FCN-VGG, and dilation convolution. Other types of LSTM modules have been proposed recently and have shown promising results for some vision tasks. Applying these newly proposed modules may enhance further the architecture of our spatio-temporal module, e.g. for scene understanding, anomaly detection in video, video captioning, object tracking, activity recognition, and so forth.

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