ICPR

Video semantic segmentation using deep multi-view representation learning

December 9, 2020

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General context

Video object segmentation

- Extract spatio-temporal regions that correspond to objects moving in the video sequence
- Two categories:
  - Graph-based approaches
  - Deep learning-based approaches.

Motivations and goals

Video object segmentation

- Existing models mainly focus on the intra-frame discrimination of primary objects in motion or appearance.
- They ignore the valuable global-occurrence consistency across multiple video frames.
- Recurrent neural networks (RNNs) fail to explore the rich relations, i.e., the high correlation between different video frames, hence do not attain a global perspective.

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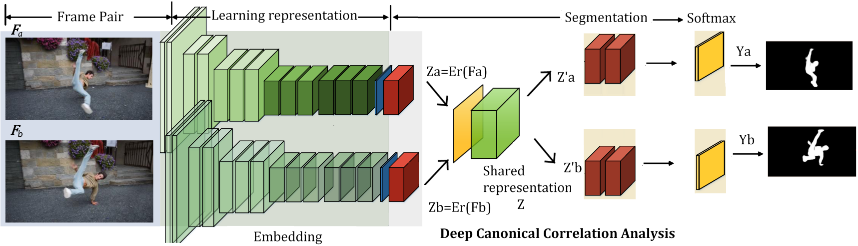
Goals

- Propose a video semantic segmentation model using deep multi-view representation learning to model video semantic segmentation task from a global view
- Capture the rich inherent correlations between all frames
- Improve the segmentation task

Multi-view deep representation learning

- Learn a better representation from pairs of frames, i.e, multimodal frames of a video by encoding their useful features in order to capture the inherent correlation between them



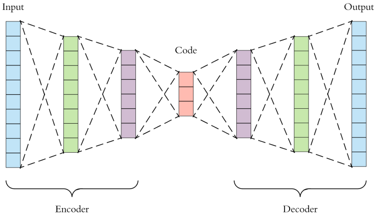
Proposed methodology

Deep canonically correlated autoencoders (DCCAE)

- Extract relevant features from multiple input modalities, i.e. pairs of video frames denoted by F_a and F_b, which may be reconstructed.
- Encode these video frames using an autoencoder (AE) model and to optimize the correlation between these video frames using the deep canonical correlation analysis (DCCA)

The AE model

- *Encoder:* Enc_{AE}
- *Bottleneck layer:* $z = Enc_{AE}(F_i)$
- *Decoder:* $Dec_{AE}(Enc_{AE}(F_i)) \approx F_i$
- *Training (MSE):*



$$\frac{1}{n \times m} \sum_{i=1}^{n} \sum_{j=1}^{m} \| Dec_{AE}(Enc_{AE}(F^{i,j})) - F^{i,j} \|^2$$

Proposed methodology

Deep Canonical Correlation analysis (DCCA)

- Find direction vectors $v_j, w_j, j \in \{1, ..., K\}$ that maximize the correlation between the projections $v_j^T Z_a$ and $w_j^T Z_b$ while being minimally redundant:

$$v_j w_j = \arg\max_{v,w} corr(v^T Z_a w^T Z_b)$$

$$\text{such that } corr(v_j^T Z_a, v_k^T Z_a) = 0, k < j$$

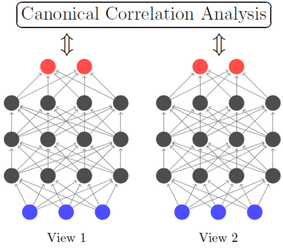
$$corr(w_j^T Z_b, w_k^T Z_b) = 0, k < j$$

$$\max_{w_f, w_g, w_p, w_q, U, V} \frac{1}{N} tr(U^T f(Z_a) g(Z_b)^T V)$$

$$\text{s.t., } U^T (\frac{1}{N} f(Z_a) f(Z_a)^T + r_{Z_a} I) U = I$$

$$V^T (\frac{1}{N} g(Z_b) g(Z_b)^T + r_{Z_b} I) V = I$$

$$u_i^T f(Z_a) g(Z_b)^T v_j = 0, \forall i \neq j$$



Proposed methodology

Deep Canonically Correlated Autoencoders (DCCAE)

- Optimize the combination of correlation between the learned latent representations (bottleneck layer) and the reconstruction errors of the AEs.

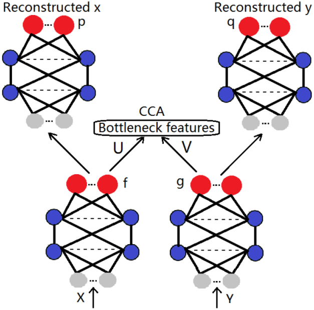
$$\min_{w_f, w_g, w_p, w_q, U, V} -\frac{1}{N} tr(U^T f(X) g(Y)^T V)$$

$$+\frac{\lambda}{N} \sum_{i=1}^{N} (||x_i - p(f(x_i))||^2) + (||y_i - q(g(y_i))||^2)$$

$$\text{s.t., } U^T(\frac{1}{N} f(X) f(X)^T + r_x I) U = I$$

$$V^T(\frac{1}{N} g(Y) g(Y)^T + r_y I) V = I$$

$$u_i^T f(X) g(Y)^T v_j = 0, \forall i \neq j$$

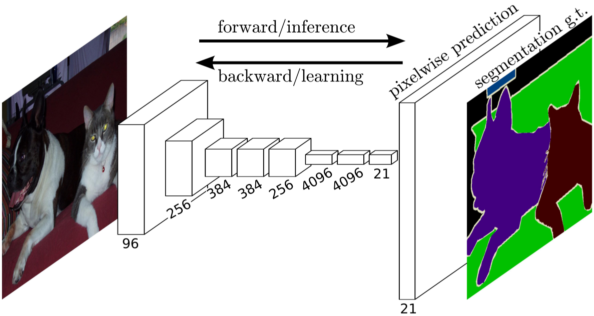


Proposed methodology

Semantic segmentation with Fully Connected Network (FCN)

- Each layer consists of three-dimensional data of size $H \times W \times C$, where W and H are spatial dimensions, and C is the channel dimension.
- The FCN compute outputs y_{ij} as follows:

$$y_{ij} = f_{ks}(\{x_{si} + \sigma_{s_i,s_j}\} \; 0 < \sigma_i, \sigma_j < k) \tag{1}$$



Experiments

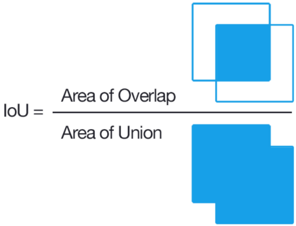
Data description

- UAVid dataset: consists of 30 video sequences capturing high-resolution images in oblique views. It is composed of 300 images and each of size 3840×2160 or 4096×2160. There are 8 classes that have been selected for semantic segmentation.
- DAVIS16 dataset: which consists of 50 videos in total. We select 30 videos for training and 20 for testing. Per-frame pixel-wise annotations are provided also.

Evaluation on UAV dataset

IoU scores for different deep learning models

Model	Building	Tree	Clutter	Road	Low Vegetation	Static car	Moving car	Human	mean IoU
FCN-8s	64.3	63.8	33.5	57.6	28.1	8.4	29.1	0.0	35.6
Dilation Net	72.8	66.9	38.5	62.4	34.4	1.2	36.8	0.0	39.1
U-Net	70.7	67.2	36.1	61.9	32.8	11.2	47.5	0.0	40.9
MS-Dilation	74.3	68.1	40.3	63.5	35.5	11.9	42.6	0.0	42.0
Ours	76.1	71.3	43.2	65.7	36.1	12.1	45.8	0.0	43.78



Evaluation on DAVIS16 dataset

Quantitative results on the test set

	Method	COSNet [36]	SFL [22]	LMP [37]	FSEG [18]	UOVO [38]	ARP [39]	PDB [25]	Ours
$\mathcal{J}$	Mean	80.5	67.4	70.0	70.7	73.9	76.2	77.2	83.3
	Recall	93.1	81.4	85.0	83.0	88.5	91.1	90.1	98.2
	Decay	4.4	6.2	1.3	1.5	0.6	7.0	0.9	0.1
$\mathcal{F}$	Mean	79.5	66.7	65.9	65.3	68.0	70.6	74.5	80.3
	Recall	89.5	77.1	79.2	73.8	80.6	83.5	84.4	94.3
	Decay	5.0	5.1	2.5	1.8	0.7	7.9	-0.2	0.0
$\mathcal{T}$	Mean	18.4	28.2	57.2	32.8	39.0	39.3	29.1	31.2

- Region similarity $\mathcal{J} = \frac{|M \cap G|}{|M \cup G|}$
- Boundary accuracy $\mathcal{F} = \frac{2 P_c R_c}{P_c + R_c}$
- Time stability $\mathcal{T}$

Conclusion and future work

- A novel deep learning model based on multi-view representation learning, to incorporate the inherent correlation between video frames during semantic segmentation
- The model based on deep canonically correlated autoencoders learns to discriminate primary objects in each frame and to capture the important correlation across video frames
- In the future, it can be extended by introducing a graph convolutional network model incorporating spatial features in order to improve the semantic segmentation.

Thank you for your attention!