

Improvement in object segmentation techniques over a live video sequence with optimal inference run-time

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Introduction

This paper deals with the improvement of segmentation techniques used for detecting objects in video sequences. A lot of work has been done in the past which have shown good segmentation results on still images. Here, I have tried to propose an extension of Mask R-CNN[7] for segmentation on video images with some inputs from OSVOS architecture[2] which segments an object along the entire video given the mask of only one single labeled sample and the classification of all the pixels of video sequence into foreground and background given the manual annotation of one or more frames.

The paper "Person identification using spatio-temporal characteristics" [5] has tried to address this segmentation approach as a development over other model-based video-object based segmentation techniques and use different skeletal data characteristics such as joints positionings and their orientation or other grid features such as stride length, grid length and other shape templates. This algorithm computes the dense trajectories based on optical flow field and their motion information is encoded using local descriptors. A codebook based on Gaussian Mixture Models is built and the features are encoded using Fischer vector. The computed features are classified using SVM to recognize the individuals. This paper although has produced significant improvements in accuracy but the feature reuse and warping used in this technique using optical flow has encountered limits in the speed up of the process.

In "Fast Semantic Segmentation on Video Using Motion Vector-Based Feature Interpolation" [1], an improvement over this existing technique has been proposed. This can be done by a two-stage approach to eliminate the process of optical flow. Here, a fast feature propagation scheme is used which utilizes the block motion vector maps to cheaply propagate features from frame to frame. Secondly, we develop a novel feature estimation scheme, termed as feature estimation, which fuses features from enclosing keyframes to render accurate estimates. In this paper, I have tried to combine the techniques used for semantic segmentation in Mask R-CNN for still images with the concept of motion vectors to detect objects in a video sequence.

Experimentation and Results

1. **Mask R-CNN[7]:** This technique adds an additional branch for predicting an object mask with an existing branch for bounding box recognition and mask prediction which is the baseline of our work. This was performed on Cityscapes dataset which contain 2975 train, 500 validation and 1525 test images using ResNet-50 FPN[4].

There are 7 categories of images in the dataset where we reduce the learning rate at every 3000 iterations and run until 4000 iterations. This gives an output of 32.0 AP on the test set, a 6 point improvement over the fine-only counterpart. The results have been shown in Table 1.

	training data	AP [val]	AP	AP ₅₀	person	rider	car	truck	bus	train	motorcycle	bicycle
InstanceCut [23]	fine+coarse	15.8	13.0	27.9	10.0	8.0	23.7	14.0	19.5	15.2	9.3	4.7
DWT [4]	fine	19.8	15.6	30.0	15.1	11.7	32.9	17.1	20.4	15.0	7.9	4.9
SAIS [17]	fine	-	17.4	36.7	14.6	12.9	35.7	16.0	23.2	19.0	10.3	7.8
DIN [3]	fine+coarse	-	20.0	38.8	16.5	16.7	25.7	20.6	30.0	23.4	17.1	10.1
SGN [29]	fine+coarse	29.2	25.0	44.9	21.8	20.1	39.4	24.8	33.2	30.8	17.7	12.4
Mask R-CNN	fine	31.5	26.2	49.9	30.5	23.7	46.9	22.8	32.2	18.6	19.1	16.0
Mask R-CNN	fine+COCO	36.4	32.0	58.1	34.8	27.0	49.1	30.1	40.9	30.9	24.1	18.7

Figure 1: Results of Mask R-CNN on Cityscapes dataset. This method uses ResNet-50 FPN [7]

2. **One Shot Video Object Segmentation(OSVOS)[2]:** This technique was performed on DAVIS dataset where 50 full HD Video sequences with all frames were segmented with pixel level accuracy. It was performed with some semi-supervised, unsupervised and Bounds techniques and have been shown in Table 2 and 3.

To further validate our results, a few manually annotated objects in a Youtube video were also taken into consideration.

Measure	Semi-Supervised										Unsupervised				Bounds			
	Ours	OFL	BVS	PCP	JMP	HVS	SEA	TSP	FST	NLC	MSG	KEY	CVOS	TBC	SAL	COBSP	COB	MCB
Mean A _t	79.8	68.0	60.0	58.4	57.0	54.6	50.4	31.9	55.8	55.1	53.3	49.8	48.2	47.3	39.3	86.5	79.3	70.7
J Recall C _t	93.6	75.6	66.0	71.5	62.6	61.4	53.1	30.0	64.9	55.8	61.6	59.1	54.0	49.3	30.0	96.5	94.4	91.7
Decay P _t	14.9	26.4	28.9	-2.0	39.4	23.6	36.4	38.1	0.0	12.6	2.4	14.1	10.5	8.3	4.9	2.8	3.2	1.8
Mean A _t	80.6	63.4	58.8	49.2	53.1	52.9	48.0	29.7	51.1	52.3	50.8	42.7	44.7	44.1	34.4	87.1	75.7	62.9
J Recall C _t	92.6	70.4	67.9	49.5	54.2	61.0	46.3	23.0	51.6	51.9	60.0	37.5	52.6	43.6	15.4	92.4	88.5	76.7
Decay P _t	15.0	27.2	21.3	-1.1	38.4	22.7	34.5	35.7	2.9	11.4	5.1	10.6	11.7	12.9	4.3	2.3	8.9	1.9
J Mean A _t	37.6	21.7	31.5	29.6	15.3	35.0	14.9	41.2	34.3	41.4	29.1	25.2	24.4	37.6	64.1	27.4	44.1	69.8

Figure 2: DAVIS Validation: OSVOS versus the state of the art, and practical bounds[2].

Category	Ours	OFL	JFS	BVS	SCF	AFS	FST	HBT	LTV
Aeroplane	88.2	89.9	89.0	86.8	86.3	79.9	70.9	73.6	13.7
Bird	85.7	84.2	81.6	80.9	81.0	78.4	70.6	56.1	12.2
Boat	77.5	74.0	74.2	65.1	68.6	60.1	42.5	57.8	10.8
Car	79.6	80.9	70.9	68.7	69.4	64.4	65.2	33.9	23.7
Cat	70.8	68.3	67.7	55.9	58.9	50.4	52.1	30.5	18.6
Cow	77.8	79.8	79.1	69.9	68.6	65.7	44.5	41.8	16.3
Dog	81.3	76.6	70.3	68.5	61.8	54.2	65.3	36.8	18.0
Horse	72.8	72.6	67.8	58.9	54.0	50.8	53.5	44.3	11.5
Motorbike	73.5	73.7	61.5	60.5	60.9	58.3	44.2	48.9	10.6
Train	75.7	76.3	78.2	65.2	66.3	62.4	29.6	39.2	19.6
Mean	78.3	77.6	74.0	68.0	67.6	62.5	53.8	46.3	15.5

Figure 3: Youtube-Objects evaluation: Per-category mean intersection over union[2].

3. Person Identification Using Spatiotemporal Motion Characteristics[5]:

To validate this technique, the results were performed on TUM GAID database (a common gait recognition database). The codebook size k was set to 32. A total of 3370 train sequences are there in the database consisting of 305 subjects. For this approach, 10 walk sequences of each subject , total of 32 subjects, were recorded using Microsoft Kinet for both Summer and Winter seasons at 30 fps. The walk sequences consisted of Normal Walk(N), Walking with Backpack(B), Walk with Shoes(S), normal walk after time (TN), walk with backpack after time (TB) and walk with coating shoes after time (TS). Many different techniques were used on this database but our proposed algorithm achieved an accuracy of 96.5 percent on the dataset bettering other classifiers. Detailed results have been shown in Table 4.

Method	N	B	S	TN	TB	TS	Avg.
GEI [17]	99.4	27.1	56.2	44.0	6.0	9.0	56.0
GEV [17]	94.2	13.9	87.7	41.0	0.0	31.0	61.4
SVIM [30]	98.4	64.2	91.6	65.6	31.3	50.0	81.4
CNN-SVM [29]	99.7	97.1	97.1	59.4	50.0	62.5	94.2
CNN-NN128 [29]	99.7	98.1	95.8	62.5	56.3	59.4	94.2
H2M [31]	99.4	100.0	98.1	71.9	63.4	43.8	95.5
DCS [31]	99.7	99.0	99.0	78.1	62.0	54.9	96.0
PFM [28]	99.7	99.0	99.0	78.1	62.0	54.9	96.0
Proposed	99.7	100	99.7	68.8	71.9	53.1	96.5

Figure 4: Performance evaluation on TUM GAID database. Avg. is the weighted average score of each method. The best results are in bold font[5].

4. Fast Semantic Segmentation on Video Using Motion Vector-Based Feature Interpolation[1]:

Here, we have considered 30 frame snippets of 50 European cities. The frame rate for this experiment was calculated to be 17fps and the image dimension was 2048X1024 pixels. The entire dataset was divided into 2975 train, 500 validation and 1525 test images. Details about the accuracy of this technique have been demonstrated in Table 5 and have been more elaborately discussed in the conclusion part as it is

the state of the art technique which we wish to modify and incorporate for live video object segmentation.

Metric	Scheme	keyframe interval									
		1	2	3	4	5	6	7	8	9	10
mIoU, avg (%)	prop-flow	75.2	73.8	72.0	70.2	68.7	67.3	65.0	63.4	62.4	60.6
	prop-mv	75.2	73.1	71.3	69.4	68.2	67.3	65.0	64.0	63.2	61.7
	interp	75.2	73.9	72.5	71.2	70.5	69.9	68.5	67.5	66.9	66.6
mIoU, min (%)	prop-flow	75.2	72.4	68.9	65.6	62.4	59.1	56.3	54.4	52.5	50.5
	prop-mv	75.2	71.3	67.7	64.8	62.4	60.1	58.5	56.9	55.0	53.7
	interp	75.2	72.5	71.5	68.0	67.2	66.2	65.4	64.6	63.5	62.9
runtime (fps)	prop-flow	1.3	2.3	3.0	3.5	4.0	4.3	4.6	4.9	5.1	5.3
	prop-mv	1.3	2.5	3.4	4.3	5.0	5.6	6.2	6.7	7.1	7.6
	interp	1.3	2.4	3.4	4.2	4.9	5.4	6.0	6.4	6.9	7.2

Figure 5: Accuracy and runtimes for optical flow-based feature propagation(propflow), motion vectors-based propagation (prop-mv), and feature interpolation (interp).[1]

Conclusion and Future Work

The main motivation behind my work is to reduce the inference run time while segmenting along a video sequence. For this, the idea of motion vector maps as a replacement to optical flow solves a part of this problem. In [1], this idea has been explained in detail. The entire frame is divided into 16X16 non-overlapping pixels. The best matching 16X16 pixel block is compared with the reference frame which is measured by the Mean Squared Error(MSE) between the data frames and the pair with the minimum MSE is stored in the Motion Vector Mapping as a (x,y) pair.

Then, the process of feature interpolation is done for a key frame interval of size n where a key frame interval refers to the number of frames between two key frames. For a key frame interval n , $n-1$ forward feature maps and $n-1$ backward feature maps are computed and all of them are fused in the end to get the optimal feature map which is then used for detection along the video sequence. This whole process when compared to that of optical flow reduces the inference run time by over 50 per cent.

The main disadvantage of this technique which I seek to solve is that in live straming, we look for n frames ahead so here, we have to look for a small delay of 30fps while segmenting along a video sequence. This may give optimal results but while segmenting in a cityscape environment where the surroundings are rapidly changing, it is difficult for us to compute the motion vectors as the spatiotemporal characteristics of the frame changes so we have to look for alternative approaches while segmenting along a live video sequence in such an environment.

In this case, OSVOS technique[2] explained earlier can prove to be handy where we can segment along the entire video sequence given the multiple annotations of single/multiple frames in a video. In future, work needs to be done to figure out how we can combine the concept of motion vector maps with OSVOS technique so that we can segment along a live video sequence without any delay and with much less computation time.

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