TapLab: A Fast Framework for Semantic Video Segmentation Tapping into Compressed-Domain Knowledge

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Abstract—Real-time semantic video segmentation is a challenging task due to the strict requirements of inference speed. Recent approaches mainly devote great efforts to reducing the model size for high efficiency. In this paper, we rethink this problem from a different viewpoint: using knowledge contained in compressed videos. We propose a simple and effective framework, dubbed TapLab, to tap into resources from the compressed domain. Specifically, we design a fast feature warping module using motion vectors for acceleration. To reduce the noise introduced by motion vectors, we design a residual-guided correction module and a residual-guided frame selection module using residuals. Compared with the state-of-the-art fast semantic image segmentation models, our proposed TapLab significantly reduces redundant computations, running around 3 times faster with comparable accuracy for 1024 × 2048 video. The experimental results show that TapLab achieves 70.6% mIoU on the Cityscapes dataset at 99.8 FPS with a single GPU card. A high-speed version even reaches the speed of 160+ FPS.

Index Terms—Semantic video segmentation, real-time, compressed domain

1 INTRODUCTION

Semantic segmentation is typically cast as pixelwise classification on unstructured images or videos. Being effective in feature representation and discriminative learning, convolutional neural networks (CNNs) [1] have been working as a popular and powerful tool for semantic segmentation. With the advent of high-resolution (e.g., 1080p and 4K) videos, conventional CNN-based segmentation approaches usually impose high computational and memory costs which hinder real-time applications. Fast semantic video segmentation with high accuracy is an urgent demand for high-resolution vision applications.

A typical way of semantic video segmentation treats a video clip as a sequence of individual frames, relying on a network for semantic image segmentation [2], [3], [4] to perform segmentation in a frame-by-frame fashion. To meet the real-time demand, such segmentation approaches usually trade off lower accuracy for faster speed by reducing the input scale or designing a lightweight network [5], [6], [7], [8], [9], [10], [11]. However, these segmentation approaches ignore the temporal continuity of videos, thereby leading to the redundant computational burden across frames [12].

In light of the above issue, a number of segmentation approaches introduce an extra temporal feature extraction module to model the continuity of neighboring frames by 3D CNNs [13], [14], RNNs [15], [16], or optical flow estimation [17], [18]. Based on the extracted temporal features, only a small portion of key frames require full segmentation, while the other frames undergo cross-frame feature propagation or label propagation. Although the above segmentation pipelines speed up their inference phase, they usually suffer the heavy cost incurred by temporal feature extraction, e.g., optical flow estimation, which is itself a bottleneck for real-time performance.

In general, videos are compressed data in the form of computer files and network streaming. In the compressed...
domain, videos already contain a rich body of motion information such as motion vectors (Mv) and residuals (Res). Recently, these compressed-domain features have been tapped in video tasks to avoid the cost incurred by video decoding and the aforementioned temporal feature extraction. Despite the fact that motion vectors are noisier (superpixel-level instead of pixel-level), such video-level tasks as video classification [19], action recognition [20] and vehicle counting [21] can tolerate the noise. On the contrary, it takes special efforts to apply coarse-grained compressed-domain features to semantic segmentation, a pixel-level task, to achieve high accuracy.

Inspired by the above observations, we propose a novel real-time semantic video segmentation framework, named TapLab, utilizing motion information from the compressed domain for efficiency. The framework consists of a semantic image segmentation network and three plug-and-play modules tailored for semantic video segmentation. Specifically, we design a fast feature warping (FFW) module that exploits motion vectors for feature and label propagation across consecutive frames. The experimental results show that this module reduces the inference time by a wide margin. To address the noise problem introduced by motion vectors, we design a residual-guided correction (RGC) module, which adaptively selects the most inconsistent region for further refinement, and furthermore, we design a residual-guided frame selection (RGFS) module to determine the hard-to-warp frames and do segmentation instead of warping for them. The experiments demonstrate these two modules are able to refine the coarse segmentation results and improve the model’s robustness. As a result, the proposed approach performs much faster and achieves competitive accuracy compared with the state-of-the-art methods, as illustrated in Fig. 4. Also, we show that our modules are generic to networks for semantic image segmentation.

In summary, the contributions of this work are two-fold. First, we propose a novel real-time semantic video segmentation framework that taps into the encoded features that already exist in videos. In addition to a CNN for semantic segmentation, the proposed framework includes three modules: a fast feature warping module to utilize the temporal continuity in videos, a residual-guided correction module to refine local regions, and a residual-guided frame selection module to select the hard-to-warp frames for segmentation. Second, the experiments demonstrate our modules are generic to a variety of segmentation networks and the framework achieves around 3× speed-up against the state-of-the-art real-time semantic segmentation networks with competitive accuracy. On the Cityscapes [22] dataset, TapLab obtains the results of 70.6% mIoU with on 1024×2048 input at 99.8 FPS with a single GPU card. A high-speed version of TapLab achieves an FPS of 160.4 with 64.4% mIoU. We also conduct experiments on an embedded platform. To our knowledge, our approach is the first one to reach more than 10 FPS on the device on 1024×2048 input.

2 RELATED WORK

2.1 Fast Image Segmentation

Driven by the development of deep CNNs, semantic segmentation approaches [3, 4, 23] based on FCN [2] have achieved surprisingly high accuracy. Recently, more works have changed the focus onto efficiency [12]. Early works [5, 6, 7] either downsample the inputs or prune the channels of their networks. ICNet [8] and BiSeNet [9] propose multi-path strategies in which a deeper path with faster downsampling is designed to extract context features while a shallower path with original scale to preserve local details. Moreover, efficient fusion modules are assigned to combine features from different paths. More recently, SwiftNet [11] and DFANet [10] propose lightweight networks with pyramid fusion or aggregation for features. However, these methods deal with images or consider a video as individual frames. Thus, they are incapable of leveraging the temporal continuity of videos.

2.2 Semantic Video Segmentation

Methods dealing with video tasks tend to capitalize on temporal continuity in videos and thus to extract various kinds of temporal features, among which optical flow is the most commonly used one [24, 25, 26, 27]. FlowNet [28] and FlowNet 2.0 [29] estimate optical flow fields based on DCNNs and are able to run at high speed, followed by many flow-based segmentation strategies [25, 26, 27]. Gadde et al. [25] employ optical flow to warp features from different layers for feature quality enhancement. Zhu et al. [26] and Xu et al. [27] utilize the efficiency of FlowNet to propagate results of key frames for model acceleration. However, due to the extra time consumed by flow estimation, these models perform on par with fast per-frame models.

The aforementioned flow-based methods rely heavily on key frame scheduling strategies. Zhu et al. [26] preset a fixed interval to determine key frames. Adaptive scheduling strategies, e.g., [29] and [27], determine key frames according to confidence scores calculated by a lightweight CNN branch. In addition to dynamic key-frame selection, Xu et al. [27] also divide a single frame into small regions and heuristically selects less confident ones to pass through the whole segmentation network. In the area of video object detection, Zhu et al. [30] also propose to warp features across adjacent frames and learn to select key regions/frames to perform refinement.

To our knowledge, TapLab is the first work to utilize the existing encoded features residual maps to select key frames and key regions, making the selection procedure training-free, generic to various datasets, and extremely fast.

2.3 Compressed-Domain Video Analysis

Recently, features from compressed data have been utilized in vision tasks such as video classification [19, 31], vehicle counting [21, 32], action recognition [20, 33], etc. Despite the fact that compressed-domain features are noisier than pixel-domain, these video-level tasks can tolerate the noise. On the contrary, it takes special efforts to apply noisy compressed-domain features to semantic segmentation, a pixel-level task, to achieve high accuracy. More recently, Jain et al. [34] design a bidirectional feature warping module with motion vectors for semantic segmentation. However, the bidirectional feature warping design produces latency and does not solve the problem of precision-degrading caused by motion vectors.
TABLE 1
Notations

|   |   |
|---|---|
| I | original RGB frame |
| I_s | shifted frame |
| Mv | motion vector |
| Res | residual map |
| R_i | the i-th region |
| f | feature map |
| p | pixel or element index |
| t | current frame index |

FFW | fast feature warping |
RGC | residual-guided correction |
RGFS | residual-guided frame selection |
φ | segmentation CNN |

THR_{RGC} | threshold for the RGC module |
THR_{RGFS} | threshold for the RGFS module |

3 METHODS

In this section, we present details of our framework TapLab. We first introduce the basics of compressed video. Next, we describe our video segmentation framework consisting of a segmentation model and three plug-and-play modules tailored for semantic video segmentation, i.e., a fast feature warping (FFW) module, a residual-guided correction (RGC) module, and a residual-guided frame selection (RGFS) module. Finally, we present the implementation details. For convenience, Table 1 summarizes the notations.

3.1 Basics of Compressed Video

In general, an encoded video stream consists of groups of pictures (GOP). A GOP can contain three types of frames: I-frame, P-frame, and B-frame. An I-frame, a coded frame independent of all other frames, marks the beginning of a GOP. A P-frame is predicted from its previous I-frame or P-frame and a B-frame is predicted from its previous and next I-frame or P-frame. A typical sequence of a GOP can be IPPBPBPBPBP.

We use videos encoded by MPEG-4 Part 2 (Simple Profile) [35], following recent work of [20] and [33] in the compressed domain. A default GOP in this standard contains an I-frame followed by 11 P-frames (no B-frame). In the compressed domain, as shown in Fig. 2, three types of data are readily available: (1) I-frames, the beginning encoded frames of each GOP, (2) motion vectors (Mv), the displacement of a P-frame from the previous frame, either an I-frame or a P-frame, and (3) residuals (Res), the difference between a P-frame and its referenced motion-compensated frame. It is worth noting that motions vectors and residuals are encoded in many popular codecs, such as MPEG, H.264, H.265. Without loss of generality, we use MPEG-4 in our experiments. The framework can be easily generalized to other codec standards.

Features in compressed domain are coarse-grained. During compression, each frame is typically divided into 16x16 macroblocks and motion vectors represent the displacement of the macroblocks. As a result, motion vectors have much lower resolution. Although previous works [19], [20], [21], [31], [32], [33] show their effectiveness in video-level classification problems, it is impractical to directly apply them to semantic segmentation, which requires pixel-level predictions. Thus, we design the following framework.

3.2 Framework

As illustrated in Fig. 3, our segmentation framework consists of a CNN for semantic image segmentation and three modules tailored for semantic video segmentation based on compressed-domain features. The CNN (baseline model) could be any network for semantic image segmentation and we choose three commonly used architectures. As for the modules, we concentrate on speeding up the segmentation for P-frames. First, to accelerate the segmentation process, we design the fast feature warping (FFW) module to propagate spatial features based on motion vectors. Second, we design the residual-guided correction (RGC) module to refine local segmentation. RGC selects the “worst” region of a current frame and performs fine segmentation for this region. Third, we design the residual-guided frame selection (RGFS) module to refine a small portion of P-frames. RGFS selects the “hard-to-warp” P-frames and sends them into the segmentation CNN adaptively.

In addition to the components, Fig. 3 shows the complete data flow of the proposed framework and the connections among different modules. After decoding, all the I-frames are directly sent to the segmentation network. As for P-frames, RGFS selects the P-frames needed to be sent to the CNN. The rest P-frames are processed with FFW and RGC.

It is worth noting that our framework has different versions. Based on the core module FFW, the RGC module and the RGFS module can be treated as plug-ins and be added to or removed from the whole framework easily. Fig. 3 only shows the most complicated case (FFW+RGC+RGFS). More combinations (FFW, FFW+RGC, FFW+RGFS) of modules are shown in Fig. 4. The plug-and-play design gives more flexibility to or removed from the whole framework easily. Fig. 3 only shows the most complicated case (FFW+RGC+RGFS).

We describe the details of each component below.

3.2.1 Baseline Segmentation Models

We start building TapLab from choosing the semantic image segmentation models. To demonstrate the effectiveness and
3.2.2 Fast Feature Warping

Considering the transformation consistency of input images and the corresponding output labels in semantic segmentation, we design the fast feature warping (FFW) module. This module takes in the previous feature maps $\mathcal{F}^{(t-1)}$ and the current motion vectors $\mathbf{Mv}^{(t)}$ and outputs the current feature maps $\mathcal{F}^{(t)}$, the warping in feature domain is equivalent to shifting in pixel domain. Thus $\mathcal{F}^{(t)}$ is defined as

$$
\mathcal{F}^{(t)}[p] = \text{FFW}(\mathbf{Mv}^{(t)}, \mathcal{F}^{(t-1)})[p] = \mathcal{F}^{(t-1)}[p - \mathbf{Mv}^{(t)}[p]],
$$

where $p = (x, y) \in H \times W$ represents the “pixel” index in the feature maps. According to Equation (1), there are just simple shifting operations during FFW, making this procedure extremely fast.

To make the procedure even faster, we could use longer GOPs. Given the GOP number $g$ and inference time $T_I, T_P$ for I-frames and P-frames respectively, the overall inference time is defined by

$$
T_{\text{avg}} = \frac{1}{g} \cdot T_I + \left(1 - \frac{1}{g}\right) \cdot T_P,
$$

which indicates that if $T_P \ll T_I$, larger $g$ makes for higher speed. We study the influence of GOP number on accuracy in Sec. 4.2.2.

Actually, optical flow based methods [26], [27] also use warping for speeding-up. We take motion vectors rather than optical flows as the input of the warping module for the following considerations. First, the use of motion vectors makes the framework faster. Motion vectors are compressed-domain features which already exist in video. They can be accessed with ease while optical flow estimation takes considerable extra time. Second, motion vectors, albeit coarse-grained (shown in Fig. 5(a)), fit the modern semantic segmentation CNN models and perform on a par with optical flow estimation in terms of segmentation accuracy, as shown in Table 3. Motion vectors store the motion information of small blocks (usually areas of $16 \times 16$ pixels), while optical flow algorithms calculate the motion information of all the pixels (shown in Fig. 5(b,c,d)). Nevertheless, most segmentation CNNs utilize pooling layers and convolution layers with strides to obtain larger receptive field and get
3.2.3 Residual-Guided Correction

In modern video coding algorithms, to handle the inevitable differences between the shifted image $I_1$ and the original one $I$, element-wise residual maps for compensation are introduced [37]. Inspired by this operation, we propose the residual-guided correction (RGC) module. This module takes residual maps as input and adaptively selects one region for fine-segmentation. The absolute value in residual maps is sufficient for feature warping. Also, experimental results demonstrate that the accuracy of flow information is not directly related to the segmentation accuracy. Fig. 5 shows the motion vector and the optical flow of a sample frame.

Despite the high efficiency, warping-based segmentation models display weak robustness, since neither motion vectors nor optical flow fields can present all kinds of movements, e.g., the appearance of new objects. Hence, previous works [24], [27] adaptively select key frames for fine-segmentation. We rethink this problem from the perspective of codec principles and design the following RGC and RGFS modules.

3.2.4 Residual-Guided Frame Selection

In addition to refining selected spatial regions, we capitalize on residual maps to adaptively select key frames that are “hard-to-warp”. For each P-frame, we calculate the frame-level residual score as

$$\text{RGFS}(\text{Res}_{(t)}) = \sum_{p \in \text{Res}_{(t)}} |\text{Res}_{(t)}[p]|. \quad (4)$$

Similar to the analysis in Section 3.2.4, the summation of absolute values in a residual map indicates the quality of the corresponding motion vector. The higher the residual score, the higher probability that the warped result is untrustworthy. In such situations, the corresponding frames are sent into the CNN for fine-segmentation.

We set a threshold $\text{THR}_{\text{RGFS}}$ for the RGFS module to select the “hard-to-warp” frames. If $\text{RGFS}(\text{Res}_{(t)}) > \text{THR}_{\text{RGFS}}$, the current P-frame is treated as a key frame. Higher $\text{THR}_{\text{RGFS}}$ indicates that the module is less sensitive to the noise of MV, and the average inference speed becomes faster due to less key frames. As a trade-off, the accuracy would decrease.

Compared with [24], [27] which apply dynamic key frame selection by adding a CNN branch to predict the confidence score, RGFS is simpler and faster. Moreover, the residual-guided modules are intuitive since residual maps are meant to offer motion compensation.

3.3 Implementation Details

Here are the implementation details of our loss function and inference algorithm.

3.3.1 Loss Function

To train the baseline segmentation CNNs, we follow the previous works and use the softmax cross entropy loss defined as

$$L = - \sum_{x=1}^{H} \sum_{y=1}^{W} \sum_{c=1}^{C} c \frac{e^{F(x,y,c)}}{\sum_{c=1}^{C} e^{F(x,y,c)}}, \quad (5)$$

where $c$ is the ground truth class.

3.3.2 Inference Algorithm

The overall inference procedure is summarized in Algorithm 1. Considering the implementation complexity, we only encode I-frames and P-frames during compression. Note
that the weights of the CNN in the RGC module are the same as those of the per-frame segmentation model.

For the RGC module, the threshold is universal for different datasets. Empirically, \( \text{THR}_{\text{RGC}} \in \{10, 20, 30, 40\} \) leads to similar performance. For the RGFS module, we choose \( \text{THR}_{\text{RGFS}} \) such that about 10% P-frames are selected as key-frames. This parameter can be adjusted to balance speed and accuracy. We choose this threshold on the training set of different datasets.

4 EXPERIMENTAL EVALUATION

In this section, we evaluate TapLab on high-resolution video. We first briefly introduce the experimental environment. Then we perform ablation study to validate the effectiveness of each module. Finally, we perform a thorough comparison of our model with the state-of-the-art fast segmentation models in terms of both accuracy and speed.

4.1 Experimental Environment

4.1.1 Datasets

There exist many commonly used datasets for the semantic segmentation task, such as Cityscapes [22], CamVid [40], COCO-Stuff [41], ADE20K [42], and so on. Considering the demand for high-resolution input and the requirement that there should be image sequences to form video clips, we choose to perform training and validation mainly on Cityscapes, a dataset for semantic understanding of urban street scenes. It contains 11 background categories and 8 foreground categories. The 5000 finely annotated images are split into training, validation and testing sets with 2975, 500, and 1525 images respectively. Each of these images is actually the 20th frame of a 30-frame video clip. All the frames have the resolution of 1024×2048.

In addition to the main ablations on Cityscapes, we also provide qualitative and quantitative results on CamVid.

4.1.2 Protocol

In our experiments, we choose MPEG-4 Part 2 (Simple Profile) [35] as the compression standard where the B-frame rate is 0. The Group of Pictures (GOP), which determines the interval for two adjacent I-frames, defaults to 12.

As for the details of our modules, we choose regions with resolution 512×512 and the stride along each axis is 256 for our RGC module. The noise threshold \( \text{THR}_{\text{RGFS}} \) for compensation map judgement is set to 30, and the threshold \( \text{THR}_{\text{RGFS}} \) for the RGFS module is set to \( 3.6 \times 10^7 \).

We evaluate the performance on the validation set. We randomly choose the interval between the starting frame and the test frame since only one frame of the 30-frame video clip is annotated. No testing augmentation like multi-scale or multi-crop is employed. We evaluate the speed and accuracy on images with the resolution of 1024 × 2048 using only the single scale model. The accuracy is measured by mean Intersection-over-Union (mIoU). All of experiments are performed on a server with an Intel Core i7-6800K CPU and a single NVIDIA Geforce GTX 1080 Ti GPU card. We use Tensorflow [43] to build the CNNs.

4.2 Ablation Study

4.2.1 Baseline

We start building our semantic video segmentation framework from the implementation of per-frame segmentation

\[ \text{Algorithm 1 Inference Procedure} \]

- **Require:**
  - The compressed video stream \( V \);
- **for** \( t = 1 \) to \( |V| \) **do**
  - if \( t \) th frame is I-type then
    - decode \( I(t) \)
    - \( \mathcal{F}(t) = \phi(I(t)) \)
  - else do
    - decode \( Mv(t), Res(t), I(t) \)
    - if \( \text{RGFS}(Res(t)) > \text{THR}_{\text{RGFS}} \) \( \Rightarrow \)
      - \( \mathcal{F}(t) = \phi(I(t)) \)
    - else do
      - \( \mathcal{F}(t) = \text{FFW}(Mv(t), \mathcal{F}(t-1)) \)
      - \( R_{1}^{(t)} = \text{RGC}(Res(t)) \)
      - \( \mathcal{F}(t)[R_{i}^{(t)}] = \phi(I(t)[R_{i}^{(t)}]) \)
  - **end do**
- **end do**
- **Output:** current segmentation result \( \mathcal{F}(t) \)

\[ \text{TABLE 2} \]

| Model     | Backbone      | mIoU | FPS |
|-----------|---------------|------|-----|
| BL1       | ResNet-50†    | 67.3 | 33.2 |
| BL2       | MobileNet     | 73.6 | 29.3 |
| BL3       | ResNet-101    | 77.3 | 7.2  |

The symbol "†" indicates that the network is a modified lightweight version. All the backbones are not pre-trained. The results are evaluated on validation set.

\[ \text{TABLE 3} \]

| Model       | \( T_{\text{flow}} (\text{ms}) \) | \( T_{\text{warp}} (\text{ms}) \) | \( T_{\text{total}} (\text{ms}) \) | mIoU |
|-------------|----------------------------------|----------------------------------|----------------------------------|------|
| BL1+ITP     | -                                | 20                               | 20                               | 36.1 |
| BL1+flow2   | 67                               | 3.7                              | 70.7                             | 61.1 |
| BL1+flow2C  | 32                               | 3.7                              | 35.7                             | 60.2 |
| BL1+flow2S  | 23                               | 3.7                              | 26.7                             | 59.8 |
| BL1+pwc     | 19                               | 3.7                              | 22.7                             | 60.4 |
| BL1+FFW     | -                                | 3.7                              | 3.7                              | 60.6 |
| BL2+ITP     | -                                | 20                               | 20                               | 42.1 |
| BL2+flow2   | 67                               | 3.7                              | 70.7                             | 62.1 |
| BL2+pwc     | 19                               | 3.7                              | 22.7                             | 61.7 |
| BL2+FFW     | -                                | 3.7                              | 3.7                              | 64.4 |
| BL3+ITP     | -                                | 20                               | 20                               | 43.1 |
| BL3+flow2   | 67                               | 3.7                              | 70.7                             | 67.5 |
| BL3+pwc     | 19                               | 3.7                              | 22.7                             | 66.8 |
| BL3+FFW     | -                                | 3.7                              | 3.7                              | 67.1 |

\( T_{\text{flow}} \): the time for extracting optical flows. \( T_{\text{warp}} \): the time for warping or interpolation. \( T_{\text{total}} \): the total running time for warping (interpolation). "ITP": interpolation method. "flow2": Flownet 2.0 [29] for optical flow estimation. "pwc": PWC-Net [18]. "FFW": the fast feature warping module.
CNN models. As described in Section 3.2.1, we implement the following three baseline models. The first one, denoted by BL1, follows the idea of multi-stream from ICNet [8]. The second one, denoted by BL2, utilizes multi-level feature aggregation from FPN [44] and U-Net [36]. The last one, BL3, utilizes the spatial pyramid pooling module proposed in PSPNet [23] with ResNet-101 as the backbone.

All of the networks mentioned follow the same training strategy. We only use the 2925 fine annotated training images for training. The models are trained with the Adam optimizer [45] with initial learning rate $2 \times 10^{-4}$, batch size 8, momentum 0.9, and weight decay $1 \times 10^{-6}$. The 'poly' learning rate policy is adopted with the power 0.9. Data augmentation includes random flipping, mean subtraction, random scaling between [0.5, 2.0], and random cropping into 800 × 800 images.

The performances of baseline models are summarized in Table 2. By default, we use BL2 as our baseline segmentation model in the following part.

4.2.2 Using the Fast Feature Warping Module

To demonstrate the effectiveness of the FFW module, we compare the motion vector-based FFW module with interpolation method and optical flow-based warping. The interpolation method obtains the segmentation result of a certain frame by linearly interpolating the segmentation results of the previous and the next key frame. The optical flow-based warping, which takes optical flows instead of motion vectors as input, is similar to FFW, but it takes extra time for optical flow estimation.

The comparison of these propagation methods is summarized in Table 3. Fig. 9 shows segmentation results w.r.t different kinds of motion inputs. The results using motion vectors are similar to those using optical flows.

from Fig. 9 that although optical flows can make the edges of objects more smooth, they are not able to handle the error accumulation caused by successive warping and the occlusion issue.

As shown in Table 3, both motion vector and optical flow-based warping achieves higher accuracy than interpolation. Compared with optical flow method, FFW saves the time of flow estimation and achieves competitive accuracy. After applying FFW, all the three baseline models get several times of speed-up while the accuracy decreases to some degree.

In addition to increasing the speed, FFW unexpectedly performs better than baseline per-frame method in some particular situations, as shown in Fig. 7. This is due to the moving of some objects through boundaries of the camera view. Per-frame method (BL1) performs worse because it lacks the contextual information outside the camera view, whereas our FFW module can benefit from features extracted by previous frames.

The results above are based on the configuration that Group of Pictures (GOP) of a video is set to 12, the default value by MPEG-4. As shown in Equation 2, the average running time of TapLab is strongly correlated with the GOP number $g$. Fig. 8 illustrates accuracy (mIoU) versus speed (FPS) under different GOP configurations.

4.2.3 Using the Region-Guided Correction Module

Noticing the important role that residual maps play in video codec for motion compensation, we propose the residual-
guided correction (RGC) module to refine the propagated features. The correction procedure is shown in Fig. 10. This improves the accuracy from 64.4% to 68.2% (BL2), as shown in Table 4. Note that to alleviate the boundary-cropping problem, we set the “stride” parameter to keep the regions overlapped. When the stride is smaller than a regions side (e.g., 256 vs. 512), the candidate regions will be overlapping instead of adjacent so that even if a high-response object is sliced by the chosen regions boundary, most of the object can stay in the region. RGC can run in parallel with FFW to avoid extra running time. As shown in Table 4 when resolution of the input region is low enough, the inference speed grows disproportionately to the shrinking rate of the input shape, which means the dominator of inference time changes from computational costs to I/O and communication operations (e.g., the time for ‘feed_dict’ in Tensorflow).

Practically, for the chosen region, we use the linear combination of warped feature maps, \( F_w \), and the feature maps re-computed by the CNN, \( F_{cnn} \), to form the final spatial feature maps, i.e.,

\[
F = (1 - \alpha) \cdot F_w + \alpha \cdot F_{cnn},
\]

where \( \alpha \) is the weight of combination. We study the effect of \( \alpha \) as shown in Fig. 11. Notice that the feature maps directly obtained by the CNN, when \( \alpha = 1 \), do not achieve higher accuracy. We argue the concavity of this curve is caused by the following reasons. On the one hand, when \( \alpha \to 1 \) or \( F_{cnn} \) dominates, the small input region cannot capture enough global information, resulting in wrong predictions. On the other hand, when \( \alpha \to 0 \), the result feature maps are obtained from FFW with a lot of noise. Thus, only when \( \alpha \) takes intermediate values, the result maps can take advantage of high responses from both.

4.2.4 Using the Residual-Guided Frame Selection Module

In addition to the correction of spatial regions, we also design the residual-guided frame selection (RGFS) module to select the “hard-to-warp” P-frames and send them into the segmentation CNN. We set \( \text{THR}_{\text{RGFS}} = 3.6 \times 10^7 \) and this will proximately bring 10% P-frames as key frames.

As expected, this module further improves the segmentation accuracy from 68.2% to 70.6% (BL2). Table 5 presents the effectiveness of different modules. Notice that for BL1 and BL2, using RGC alone is faster than using RGFS alone while for BL3, it is the other way around. This is due to the slow BL3. It takes more time for BL3 to do region (512 x 512) segmentation for every single frame in RGC than to do full-size segmentation for 10% P-frames in RGFS.

Moreover, it is worth noting that our RGC and RGFS modules can be applied under all the GOP settings. As shown in Table 6 when GOP number is large, the accuracy get improved with only little more time consumed. To summarize, the RGC and RGFS modules are generic to different settings of GOP numbers.

4.2.5 Qualitative Results

The qualitative results of our framework on samples of Cityscapes are shown in Fig. 12. FFW speeds the process of segmentation but also introduces noise to the results. With the addition of RGC and RGFS, we obtain segmentation results with higher quality.

4.3 Comparison with Other State-of-the-Art Methods

Finally, we compare our proposed framework with other state-of-the-art methods on Cityscapes validation set as
Fig. 12. Results on the Cityscapes dataset. Despite the fact that FFW speeds up the segmentation, it also introduces noise in the results. With the help of RGC and RGFS, the boundaries of objects become much clearer.

Table 6
Comparison of different GOP numbers.

| GOP | Modules            | mIoU   | FPS  |
|-----|--------------------|--------|------|
| 3   | FFW                | 71.9   | 72.2 |
|     | FFW+RGC+RGFS      | 72.5 (+0.6) | 67.2 |
| 6   | FFW                | 69.3   | 114.0|
|     | FFW+RGC+RGFS      | 71.5 (+2.2) | 86.3 |
| 9   | FFW                | 67.4   | 141.2|
|     | FFW+RGC+RGFS      | 71.0 (+3.6) | 93.5 |
| 12  | FFW                | 64.4   | 160.4|
|     | FFW+RGC+RGFS      | 70.6 (+6.2) | 99.8 |

The effectiveness of RGC and RGFS in different settings of GOP numbers.

shown in Table[7] We conduct all the experiments on a server with an Intel Core i7-6800K CPU and a single NVIDIA GeForce 1080 Ti GPU card. All our models run on the platform with CUDA 9.2, cuDNN 7.3 and Tensorflow 1.12. For fair comparison, we follow the recent work of [11] and include the column “FPS norm”, which provides a rough estimate on methods evaluated on other platforms and different resolutions. We use the scaling factors from the publicly available GPU benchmarks[1]. The scaling factors are 1.0 for GTX 1080 Ti, 1.07 for TITAN Xp, 0.97 for TITAN X Pascal, 0.61 for TITAN X Maxwell, 0.46 for TITAN, and 0.44 for K40. As shown in Table[7] our framework reaches impressive speed with comparable accuracy.

4.4 Results on Camvid
In this section, we provide qualitative and quantitative results on the Camvid dataset[40], which contains video sequences at the resolution of 720 × 960. We use the commonly used split, which partitions the dataset into 367 and 233 images for training and testing. During evaluation, 11 semantic classes are taken into account.

The training protocol is the same as that of Cityscapes except for the crop size set to 600 × 600 and we train the model for 20000 steps. The threshold THR_{RGC} is set to 30. The threshold for frame selection THR_{RGFS} is set to 1.8 × 10^7 to keep 10% P-frames selected by RGFS for full-resolution segmentation.

Table[8] and Fig.[13] show the quantitative and qualitative results of TapLab on Camvid. Without loss of generality, we use BL2 as the baseline model. According to the results, our TapLab achieves consistent results on this dataset. Note that the changes between adjacent frames are slight, since the frequency of videos in Camvid (30 Hz) is higher than that in Cityscapes (17 Hz). Thus, the accuracy degradation incurred by applying warping is smaller.

4.5 Evaluation on Embedded System
We conduct experiments on an embedded system. We report the results of the inference speed on the NVIDIA Jetson TX2 platform, as shown in Table[9]. To the best of our knowledge, our model is the first one to achieve more than 10 FPS on
TABLE 7
Comparison of Different Video Segmentation Methods

| Model               | eval set | mIoU   | resolution | GPU      | FPS    | FPS norm |
|---------------------|----------|--------|------------|----------|--------|----------|
| **Per-frame Models**|          |        |            |          |        |          |
| SegNet [6]          | val      | 57.0   | 256×512    | TITAN    | 16.7   | 36.3     |
| ENet [7]            | test     | 58.3   | 512×1024   | TITAN X  | 76.9   | 79.3     |
| SQ [46]             | test     | 59.8   | 1024×2048  | TITAN X(M)| 16.7   | 27.4     |
| ICNet [8]           | val      | 67.7   | 2048×1024  | TITAN X(M)| 30.3   | 49.7     |
| BiSeNet [9]         | val      | 69.0   | 768×1536   | TITAN X(M)| 105.8  | 98.8     |
| ESPNet [47]         | test     | 60.3   | 512×1024   | TITAN X  | 112    | 115.5    |
| ERFNet [48]         | test     | 68.0   | 512×1024   | TITAN X(M)| 11.2   | 18.4     |
| DFANet [10]         | test     | 71.3   | 1024×1024  | TITAN X(M)| 100    | 103.0    |
| SwiftNet [11]       | val      | 70.4   | 1024×2048  | TITAN X  | 39.9   | 39.9     |
| BL1                 | val      | 67.3   | 1024×2048  | TITAN X  | 33.2   | 33.2     |
| BL2                 | val      | 73.6   | 1024×2048  | TITAN X  | 29.3   | 29.3     |
| BL3                 | val      | 77.3   | 1024×2048  | TITAN X  | 7.2    | 7.2      |
| **Non-Per-Frame Models**|          |        |            |          |        |          |
| DFF [26]            | val      | 69.2   | 512×1024   | Tesla K40| 5.6    | 12.8     |
| Low-Latency [24]    | val      | 75.89  | 1024×2048  | -        | 8.4    | -        |
| DVSNet1 [27]        | val      | 63.2   | 1024×2048  | 1080 Ti  | 30.4   | 30.4     |
| DVSNet2 [27]        | val      | 70.4   | 1024×2048  | 1080 Ti  | 19.8   | 19.8     |
| **TapLab**          |          |        |            |          |        |          |
| BL1+F FW            | val      | 60.6   | 1024×2048  | 1080 Ti  | 169.5  | 169.5    |
| BL1+F RW+RGC        | val      | 63.4   | 1024×2048  | 1080 Ti  | 137.5  | 137.5    |
| BL1+F RW+RGFS       | val      | 63.8   | 1024×2048  | 1080 Ti  | 123.5  | 123.5    |
| BL1+F RW+RGFS+RGC   | val      | 64.7   | 1024×2048  | 1080 Ti  | 106.9  | 106.9    |
| BL2+F FW            | val      | 64.4   | 1024×2048  | 1080 Ti  | 160.4  | 160.4    |
| BL2+F RW+RGC        | val      | 68.2   | 1024×2048  | 1080 Ti  | 131.4  | 131.4    |
| BL2+F RW+RGFS       | val      | 69.2   | 1024×2048  | 1080 Ti  | 114.0  | 114.0    |
| BL2+F RW+RGFS+RGC   | val      | 70.6   | 1024×2048  | 1080 Ti  | 99.8   | 99.8     |
| BL3+F FW            | val      | 67.1   | 1024×2048  | 1080 Ti  | 67.1   | 67.1     |
| BL3+F RW+RGC        | val      | 72.2   | 1024×2048  | 1080 Ti  | 61.4   | 61.4     |
| BL3+F RW+RGFS       | val      | 72.0   | 1024×2048  | 1080 Ti  | 38.3   | 38.3     |
| BL3+F RW+RGFS+RGC   | val      | 74.5   | 1024×2048  | 1080 Ti  | 36.5   | 36.5     |

Results of semantic segmentation on Cityscapes. We select the best results of our models evaluated on the validation and compare them with previous works. We also report the inference speed, the input resolution, and the GPU platform. The default configurations of models are reported in Section 4.2.1 and Section 4.3.

TABLE 8
Performance of Taplab on Camvid.

| FFW        | RGC | RGFS | mIoU  | FPS   |
|------------|-----|------|-------|-------|
| ✓          |     |      | 73.5  | 83.3  |
| ✓          | ✓   |      | 68.0  | 470.6 |
| ✓          | ✓   | ✓    | 70.0  | 470.6 |
| ✓          | ✓   | ✓    | 70.4  | 327.9 |
| ✓          | ✓   | ✓    | 71.2  | 246.9 |

FFW: Fast Feature Warping; RGC: Residual-Guided Correction; RGFS: Residual-Guided Frame Selection. “✓” means the method utilizes this module.

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In this paper, we present a novel compressed feature-based framework to perform semantic video segmentation effectively. It incorporates a fast feature warping module, a residual-guided correction module and a residual-guided frame selection protocol as key components to strike a balance between accuracy and speed. The modules are generic to most kinds of existing CNNs for segmentation, and they can easily be added or not to meet the actual hardware requirements. Experimental results on Cityscapes demonstrate that our framework is much more efficient than existing models. In the future, we will explore more ways to utilize compressed-domain features to improve accuracy.

5 CONCLUSION

In this paper, we present a novel compressed feature-based framework to perform semantic video segmentation effectively. It incorporates a fast feature warping module, a residual-guided correction module and a residual-guided frame selection protocol as key components to strike a balance between accuracy and speed. The modules are generic to most kinds of existing CNNs for segmentation, and they can easily be added or not to meet the actual hardware requirements. Experimental results on Cityscapes demonstrate that our framework is much more efficient than existing models. In the future, we will explore more ways to utilize compressed-domain features to improve accuracy.

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Fig. 13. Qualitative results on the Camvid dataset. The results are consistent with those on Cityscapes.

| Model                        | 480 × 320 ms FPS | 640 × 360 ms FPS | 1280 × 720 ms FPS | 1920 × 1080 ms FPS |
|------------------------------|------------------|------------------|-------------------|-------------------|
| SegNet* [6]                 | 757              | 1.3              | -                 | -                 |
| ENet* [7]                   | 47               | 21.1             | 69                | 14.6              |
| SkipNet-ShufeNet [12]       | -                | -                | 66.6              | 15.0              |
| SwiftNetRN18 [11]           | 57.1             | 17.5             | 86.2              | 11.6              |
| SwiftNetMN-V2 [11]          | 43.1             | 23.2             | 61.7              | 16.2              |
| TapLab (BL1)                | 125              | 8                | 160               | 6.25              |
| TapLab (BL1+FFW)            | **14.08**        | **71.01**        | **17.92**         | **55.81**         |

Best results are highlighted in bold. “BL1” represents our first baseline model. “FFW” refers to the faster feature warping module. “*” means the inference time is calculated on TX1.

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