Learn to See by Events: 
RGB Frame Synthesis from Event Cameras

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Abstract

Event cameras are biologically-inspired sensors that gather the temporal evolution of the scene, capturing only pixel-wise brightness variations. Despite having multiple advantages with respect to traditional cameras, their use is still limited due to the difficult intelligibility and restricted usability through traditional vision algorithms. To this aim, we present a framework which exploits the output of event cameras to synthesize RGB frames. In particular, the frame generation relies on an initial or a periodic set of color key-frames and a sequence of intermediate event frames, i.e. gray-level images that integrate the brightness changes captured by the event camera during a short temporal slot. An adversarial architecture combined with a recurrent module is employed for the frame synthesis. Both traditional and event-based datasets are adopted to assess the capabilities of the proposed architecture: pixel-wise and semantic metrics confirm the quality of the synthesized images.

1. Introduction

Event cameras, biologically-inspired optical sensors capable of asynchronously capturing pixel-wise brightness variations, i.e. events, are gaining more and more attention from the computer vision community due to their extremely high temporal resolution, low power consumption, reduced data rate, and high dynamic range [8]. Moreover, event cameras filter out redundant information as their data embodies only the temporal dynamics of the recorded scene, ignoring static and non-moving areas. In contrast, standard intensity cameras with an equivalent frame rate are able to acquire the whole complexity of the scene, including textures and, in particular, colors. On the contrary, they usually require a huge amount of memory to store the collected data, along with an high power consumption and a lower dynamic range [20]. Therefore, it would be desirable to conjugate the aforementioned advantages of event cameras with the wealthy content of intensity frames. In particular, it would be interesting to directly apply some of the computer vision algorithms initially developed for standard images on event data, without the need of redesign or collect additional expensive data.

In this paper, we investigate the joint capabilities of generative deep learning models and event cameras to correctly interpolate frames acquired by a low-rate color camera. Specifically, we explore the use of the deterministic Conditional GAN paradigm in conjunction with a recurrent network to predict RGB frames, relying on an initial or a periodic set of color key-frames and a sequence of event frames, i.e. frames that collect the information captured by event cameras in a certain amount of time.
As a case study, we embrace the automotive context, in which event cameras have the potentiality to cover a variety of applications. For instance, the growing number of high-quality cameras placed on recent cars implies the use of a large bandwidth in the internal and the external network: sending only key-frames and events might be a way to reduce the bandwidth requirements, still maintaining a high temporal resolution.

Finally, we probe the feasibility of the proposed model testing it on three different datasets which have been publicly released for the automotive context, namely DDD17 [3], Cityscapes [5], and Kitti [10].

Summarizing, our contributions are threefold:

- We investigate the use of deterministic conditional GANs to jointly handle event-based data in the form of event frames and traditional images;
- We propose a framework that performs the synthesis of color frames. To the best of our knowledge, this work represents the first attempt to exploit the generation capabilities of deep learning approaches to generate color frames relying on brightness-wise event data;
- We probe the effectiveness of the introduced architecture employing three well-known public automotive datasets, investigating the ability of the model to generate realistic images, preserving objects and semantic information of the scene.

2. Related Work

Event-based vision, i.e., the research field of the computer vision applied to event cameras, is relatively recent. A brief analysis about related methods and tasks is reported for a better understanding of the contributions of this paper.

Event-based vision. Recently, event-based vision has attracted the attention of the computer vision community. In the last years, event-based cameras, also known as event-based Dynamic Vision Sensors (DVSs) [18], have been mainly explored for monocular [30] and stereo depth estimation [1, 41], optical flow prediction [8], visual odometry [42], and SLAM [26], as well as for real time feature detection and tracking [29, 23] and ego-motion estimation [20, 7]. Moreover, various classification tasks were addressed employing event-based data, as classification of cards [28], faces [17], characters [27], and gestures [19]. The combination of deep learning methods and event-based data was also proved successful for the control of robots in a predator/prey scenario [24].

Recently, few works focused on reconstruct intensity images from event cameras, but none of them has proposed deep learning-based approaches. Bardow et al. [2] proposed an approach to simultaneously estimate the optical flow and the brightness of the recorded scene. In [32], a manifold regularization method was used in order to reconstruct intensity images. However, predicted intensity images exhibit significant visual artifacts and a relatively high noise. Moreover, these works were qualitatively analyzed only, thus a fair comparison is impracticable. An investigation on color simulations and measurements from event data was proposed in [25]. Kim et al. [14] proposed a method to simultaneously mosaicing and tracking a scene using an event camera. This approach is based on the assumption that the acquired scene is still and only the camera is changing its position.

On the contrary, in this paper we investigate the synthesis of RGB frames by employing a deep learning-based approach that analyzes both intensity and event data. Furthermore, we propose different evaluation metrics in order to assess the quality of the synthesized frames, applying them on both traditional and event-based datasets.

Conditional GANs The use of GANs in a conditional setting has been proved as a effective technique in various computer vision fields, like the future frame prediction [21], the domain transfer [40] and adaptation [37], and the image-to-image translation [13]. First GAN-based approaches [12] achieved astonishing results, but they have limited generalization capabilities, as they have been tailored for specific applications and data domains. Moreover, these methods need paired data in order to be trained.

Recently, unpaired image-to-image translation methods have been successfully proposed [44, 15]. The great advantage of working with unpaired data is counterbalanced by the limited ability to alter the input, since this kind of models works better in tasks that do not require geometric transformation, i.e., where input images are quite aligned to the output ones [44]. In this paper, we investigate how to exploit deterministic Conditional GANs in order to synthesize color frames relying on event-based data and intensity key-frames.

3. Mathematical Formulation

In this section, we present base definitions and mathematical notations of events and event frames, together with their relation to intensity images, and the proposed task, i.e., the intensity frame synthesis.

3.1. Event Frames

Following the notation proposed in [20], the $k$–th event $e_k$ captured by an event camera can be represented as

$$e_k = (x_k, y_k, t_k, p_k)$$  \hspace{1cm} (1)

where $x_k$, $y_k$, and $t_k$ are the spatio-temporal coordinates of a brightness change and $p_k \in \{-1, +1\}$ specifies the polarity of this change, which can be either positive or negative.
3.2. Intensity Frame Synthesis

The goal of the proposed approach consists in learning a parametric function

$$\Gamma : \mathbb{R}^{c \times (t+1) \times w \times h} \rightarrow \mathbb{R}^{c \times w \times h}$$

(3)

that takes as input a $c$-channel intensity image $I_t \in \mathbb{R}^{c \times w \times h}$ captured at time $t$ and an event frame $\Phi_r(t)$, which combines pixel-level brightness changes between times $t$ and $t + \tau$, and outputs the predicted intensity image $\tilde{I}(t + \tau) \in \mathbb{R}^{c \times w \times h}$ at time $t + \tau$. Here, $w$ and $h$ represent the width and the height of both intensity images and event frames. It follows that

$$\tilde{I}(t + \tau) = \Gamma(I(t), \Phi_r(t), \theta)$$

(4)

where $\theta$ corresponds to the parameters of the function $\Gamma$, that we define as the combination of multiple parametric functions in Section 4.

3.3. Difference of Images as Event Frames

Event cameras are naturally triggered by pixel-level logarithmic brightness changes and thus they provide some output data only if there is a relative movement between the sensor and the objects in the scene [9]. For small time intervals, i.e., small values of $\tau$, the brightness variation can be approximated with a first-order Taylor function as:

$$\lim_{\tau \to 0} \frac{\delta L}{\delta \tau} \approx \log(Br(I(t + \tau))) - \log(Br(I(t)))$$

(5)

where $L(t) = \log(Br(I(t)))$, $I(t)$ is the image acquired at time $t$ and $Br(\cdot)$ is a function to convert a $c$-channel image into the corresponding single-channel brightness. In the experiments, for instance, RGB images are converted into brightness images using the standard channel weights defined as $[0.299, 0.587, 0.114]$.

Therefore, an event frame $\Phi_r(t)$ can be approximated as follows:

$$\Phi_r(t) \approx \Delta L = \log(Br(I(t + \tau))) - \log(Br(I(t)))$$

(6)

Thanks to this assumption, given two intensity frames $I(t)$ and $I(t + \tau)$, it is possible to retrieve the corresponding event frame $\Phi_r(t)$ for small values of $\tau$. However, since intensity frames have more than one channel (e.g., three channels for RGB images), $I(t + \tau)$ cannot be analytically obtained given $I(t)$ and $\Phi_r(t)$.

4. Implementation

An overview of the proposed architecture is depicted in Figure 2. The framework integrates two main components. The first one – the Generative Module – receives an intensity image $I(t)$ and an event frame $\Phi_r(t)$ as input and synthesizes the frame $I(t + \tau)$ as output.
The second one – the **Recurrent Module** – refines the output of the Generative component, relying on the temporal coherence of a sequence of frames.

### 4.1. Generative Module

We follow the conditional GAN paradigm [22, 13] for the designing of the generative module. The module consists of a generative network $G$ and a discriminative network $D$ [12, 22]. Exploiting the U-Net architecture [33], $G$ is defined as a fully-convolutional deep neural network with skip connections between layers $i$ and $n - i$, where $n$ is the total number of layers. The discriminative network proposed by [13] is employed as $D$. From a mathematical perspective, $G$ corresponds to an estimation function that predicts the intensity frame $\tilde{I}(t + \tau) = G(I(t) \oplus \Phi_r(t))$ from the concatenation of an intensity frame and an event frame at time $t$ (cfr. Equation 4), while $D$ corresponds to a discriminative function able to distinguish between real and generated frames. The training procedure can be formalized as the optimization of the following min-max problem:

$$\min_{\theta_G} \max_{\theta_D} \mathbb{E}_{x \sim p(x), y \sim p(y)} \left[ \log D(x, y) \right] + \mathbb{E}_{x \sim p(x)} \left[ \log (1 - D(x, G(x))) \right]$$

where $D(x, y)$ is the probability of being a real frame and $1 - D(x, G(x))$ is the probability to be a synthesized frame, $p(x)$ is the distribution of concatenated frames $I(t) \oplus \Phi_r(t)$, and $p(y)$ is the distribution of frames $\tilde{I}(t + \tau)$. This approach leads to a Generative Module $G$ which is capable of translating pixel intensities accordingly to an event frame and producing output frames that are visually similar to the real ones.

### 4.2. Recurrent Module

The architecture of the **Recurrent Module** $R$ is a combination of an encoder-decoder architecture and a **Convolutional LSTM** (ConvLSTM) module [39]. We adopt the same U-Net architecture of the Generative Module and we insert a 512-channel dual-layer ConvLSTM block in the middle of the hourglass model. During the training phase, the Recurrent Module receives as input a sequence of frames produced by the Generative Module and outputs a sequence of the same length, sequentially updating the internal state. The activation of each ConvLSTM layer can be defined as follows:

$$I_s = \sigma(W_i \ast X_s + U_i \ast H_{s-1} + b_i)$$  \hspace{1cm} (8)

$$F_s = \sigma(W_f \ast X_s + U_f \ast H_{s-1} + b_f)$$  \hspace{1cm} (9)

$$O_s = \sigma(W_o \ast X_s + U_o \ast H_{s-1} + b_o)$$  \hspace{1cm} (10)

$$\hat{C}_s = \tanh(W_c \ast X_s + U_c \ast H_{s-1} + b_c)$$  \hspace{1cm} (11)

$$C_s = F_s \odot C_{s-1} + I_s \odot G_s$$  \hspace{1cm} (12)

$$H_s = O_s \odot \tanh(C_s)$$  \hspace{1cm} (13)

where, $I_s, F_s, O_s$ are the gates, $C_s, C_{s-1}$ are the memory cells, $G_s$ is the candidate memory, and $H_s, H_{s-1}$ are the hidden states. Each $b$ is a learned bias, each $W$ and $U$ is a learned convolutional kernel, and $X_s$ corresponds to the input. Finally, $\ast$ represents the convolutional operator and $\odot$ is the element-wise product. The underlying idea is that while the Generative Module learns how to successfully combine intensity and event frames, the Recurrent Module, capturing the context of the scene and its temporal evolution, learns to visually refine the synthesized frames, removing artifacts, enhancing colors, and improving the temporal coherence.

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**Figure 3:** Sample output frames from *Kitti* dataset. The ground truth is placed on the first column, then the output of the **Generative Module** without (G*) and with (G) the discriminator (cfr. Section 4.1) and finally the output of the **Recurrent Module** (R), that is able in particular to preserve more realistic colors, enhance contrast and reduce visual artifacts.
5. Framework Evaluation

In this section, we present the datasets used to train and test the proposed framework. Then, we describe the evaluation methods that have been employed to assess the quality of the synthesized frames, followed by the report of the experimental results and their analysis.

5.1. Datasets

Due to the recent commercial release of event cameras, a shortage of publicly-released event-based datasets is currently available in the literature. Some event-based datasets have been recently released [43, 26], but they still lack on the variety and the quality of data and annotations. These considerations have motivated us to exploit the mathematical results presented in Section 3.3 in order to take advantage of well-known public datasets, which are richer in terms of annotations and data quality, along with a recent event-based dataset.

DDD17. Binas et al. [3] introduced DDD17: End-to-end DAVIS Driving Dataset, which is the first open dataset of annotated DAVIS driving recordings. The DDD17 has over 12 hours of annotated image sequences captured by a DAVIS sensor [4] and includes both gray-level frames and event data. Sequences are captured in urban and highway scenarios, during day and night and under different weather conditions. This dataset presents some drawbacks: the very low quality of the gray-level images, due to the high noise; the limited spatial resolution (346 × 260) of the acquired frames; the impossibility to retrieve color information; the constant frame-rate (from 10 up to 50 fps) with the resulting inaccurate temporal alignment between event data and gray-level frames. Similar to [20], experiments are carried out selecting only a subset of the dataset. In particular, we employ sequences labelled as acquired during day, day wet, and day sunny.

Kitti. The Kitti Vision Benchmark Suite was introduced in [11] by Geiger et al. In this work, we use the KITTI raw [10] subset, which includes 6 hours of 1242 × 375 rectified RGB image sequences captured on different road scenarios with a good temporal resolution (10Hz). The dataset

### Table 1: Pixel-wise metrics computed on the synthesized frames with Kitti, Cityscapes (CS) and DDD17 datasets.

| Dataset  | Model | Norm ↓ | Difference ↓ | RMSE ↓ | Threshold ↑ | Indexes ↑ |
|----------|-------|--------|--------------|--------|-------------|-----------|
|          |       | $L_1$ | $L_2$ | Abs | Sqr | Lin | Log | Scl | 1.25 | 1.25 $^2$ | 1.25 $^3$ | PSNR | SSIM |
| Kitti     | G*    | .034  | .1095 | .125 | .006 | .048 | .472 | .463 | .782 | .940 | .981 | .966 | .991 |
|          | G     | .030  | .1095 | .125 | .006 | .048 | .472 | .463 | .782 | .940 | .981 | .966 | .991 |
|          | G+R   | .029  | .1071 | .105 | .005 | .046 | .194 | .191 | .846 | .968 | .991 | .966 | .991 |
| CS       | G     | .019  | 4.534 | .086 | .003 | .025 | .232 | .211 | .877 | .974 | .992 | .966 | .962 |
|          | G+R   | .015  | 4.192 | .059 | .002 | .023 | .172 | .170 | .968 | .997 | .999 | .966 | .971 |
| DDD17    | G     | .034  | 13.43 | .165 | .012 | .061 | 3.64 | 3.58 | .779 | .852 | .886 | .902 | .930 |
|          | G+R   | .032  | 13.58 | .155 | .012 | .061 | 3.50 | 3.44 | .787 | .857 | .889 | .902 | .930 |

The framework is trained in two consecutive steps. In the first phase, the Generative Module $G$ is trained following the adversarial approach detailed in Section 4.1. We optimize the network using Adam [16] with learning rate 0.0002, $\beta_1 = 0.5$, $\beta_2 = 0.99$, and a batch size of 8. In order to improve the stability of the training process, the discriminator is updated every 8 training steps of the generator. The objective function of $D$ is the common binary categorical cross entropy loss, while the objective function of $G$ is a weighted combination of the adversarial loss (i.e. the binary c.c.e) and the Mean Squared Error (MSE) loss. In the second phase, the Recurrent Module $R$ is trained while keeping the parameters of the generative module fixed. We apply the Adam optimizer with the same hyperparameters we used for the generative module, with the exception of the batch size which is set to 4. The objective function of the module is a weighted combination of the MSE and the Structural Similarity index (SSIM) loss [38]. The losses are combined with a weight of 0.5 each. The network is trained with a fixed sequence length, which corresponds to the length of the sequences used during the evaluation phase.

Only during the testing phase, to obtain a sequence of synthesized frames, the framework receives as input the previously generated images or an intensity key-frame.
is rich of annotations, as depth maps (collected through a LIDAR scanner), semantic segmentation, and object detection. We adopt the splits for train and validation data reported in [36].

Cityscapes. Introduced in [5], the Cityscapes dataset consists of a great amount of RGB frames with a high spatial resolution ($2048 \times 1024$) collected on 50 German and Swiss cities, capturing varying and complex scene layouts and backgrounds. Annotations are provided at different granularity: fine and coarse annotations of 30 different object classes are provided as both semantic and instance-wise segmentation. We select a particular subset, namely leftImg8bit sequence, in order to work on sequences with a good frame rate (17Hz) and fine semantic segmentation annotations.

5.2. Metrics

Inspired by [6, 13], we exploited a variety of metrics to check the quality of the generated images, being aware that evaluating synthesized images is in general a difficult and still open problem [35]. Pixel-wise error metrics are not able to highlight semantic or structural problems of the generated images. Therefore, we firstly design a set of experiments in order to investigate the contribution of each single module into the proposed framework by using pixel-wise metrics. Then, we exploit off-the-shelf networks pre-trained on public datasets in order to perform semantic segmentation and object detection on generated images. Through these tests, we aim to verify the capability of the proposed framework to preserve objects and semantic information in the synthesized frames, which is mandatory for employing the proposed method in real world scenarios. Finally, the realism of synthesized images are globally evaluated through a “real vs fake” and a “fake vs fake” perceptual study.

**Table 2: Semantic Segmentation and Object Detection scores computed on the synthesized frames with Kitti and Cityscapes datasets.** Tests are carried out using the Generative Module (G) in combination with the Recurrent Module (G+R). Results are compared with the Ground Truth (GT) when available.

| Dataset | Model | Semantic Seg. ↑ | Object Det. ↑ |
|---------|-------|----------------|--------------|
|         | Per-pixel | Per-class | class IoU | mIoU | % |
| Kitti   | G     | .814 | .261 | .215 | .914 | .658 |
|         | G+R   | .813 | .261 | .215 | .911 | .699 |
|         | GT    | .827 | .283 | .235 | - | - |
| CS      | G     | .771 | .197 | .162 | .925 | .795 |
|         | G+R   | .790 | .201 | .166 | .926 | .822 |
|         | GT    | .828 | .227 | .192 | - | - |

Pixel-wise metrics. As stated above, a collection of per-pixel evaluation metrics is used to assess the quality of the synthesized images. In particular, we report the $L1$ and $L2$ distance, the absolute and the squared relative difference, the root mean squared error (RMSE), and the percentage of pixel under a certain error threshold ($\delta$-metrics).

Further details about these metrics are reported in [6]. Moreover, we include the Peak Signal-to-Noise Ratio (PSNR), which estimates the level of noise in the final generated frames in logarithmic scale, and the Structural Similarity index (SSIM) [38], which predicts the perceived quality of the synthesized frames.

**Semantic segmentation score.** We adopt a pre-trained semantic classifier to measure the accuracy of a certain set of pixels to be a particular class. If synthesized images are close to the real ones, the classifier will achieve a comparable accuracy to the one obtained on the reference dataset. We adopt the recent state-of-art WideResNet+38+DeepLab3 [34] trained on the original annotations of the Cityscapes dataset. Since a fine annotation of the semantic segmentation is provided only for a limited subset of frames in each sequence, we compare these annotations with the semantic maps produced using as input the last frame of a synthesized sequence.
**Object detection score.** In addition, a pre-trained object detector is employed in order to investigate if the proposed model is able to preserve details, locations, and realistic aspect of the objects that appear in the scene. We adopt the popular Yolo network \[31\], a real-time state-of-the-art object detection system. In this way, since we use automotive datasets, we investigate the ability of the proposed framework to preserve objects in the generated frames, in particular cars, trucks, pedestrians, bicycles, bus, motorbikes, and stop signals.

**Perceptual validation.** Proposed metrics try to assess the perceptual realism that usually belongs to humans. Therefore, we believe that including validations produced by humans is an additional valuable test, which can probe the effectiveness of the proposed framework in generating realistic images. We run a test in which a series of 25 real (i.e. original) and fake (i.e. synthesized) frame sequences, taken randomly from the aforementioned datasets, are shown. Users were asked to choose the most realistic sequence in a limited amount of time. 50 users have been randomly chosen in a set of people which were unaware of the task and deep learning-based techniques for image generation. Similar to \[13\], we do not include vigilance supervision.

### 5.3. Experimental Results

We deeply investigate the quality of the images synthesized by the proposed framework. For a fair comparison, we empirically set the same sequence length of 6 synthesized frames for every experiment reported in this section. We adapt the image resolution of the original data (different for each dataset) to comply with the U-Net architecture (cfr. Section 4.1) requirements while trying to keep the original image aspect ratio. Therefore, we adopt input images with a spatial resolution of 256 $\times$ 128 for Cityscapes, 416 $\times$ 128 for Kitti and 256 $\times$ 192 for DDD17.

Table 1 shows the pixel-wise metrics. In particular, we exploit these metrics in order to understand the contribution of each single module, i.e. the Generative Module, the discriminator, and the Recurrent Module. We found that the output of the Generative Module has a good level of quality and learns efficiently to alter pixel values accordingly to event frames. Recurrent Module visually boosts the final output frames, enhancing colors and improving the contrast, the level of details, and the temporal coherence (Figure 3). Generally, we note that the low quality of the gray-level images belonging to the DDD17 dataset partially influences the performance of the framework.

In Table 2, results are reported in terms of Per-pixel, Per-class, and IoU accuracy for the Semantic Segmentation score and in terms of mean IoU and percentage of the correctly detected objects for the Object Detection one. Segmentation results confirm that our approach can be a valid option to avoid the developing of completely new vision algorithms relying on event data. Also in this case, the Recurrent Module improves the final score.

Table 2 includes also the Object Detection scores, in terms of mean IoU on detection bounding boxes and the percentage of object detected with respect to the ground truth, i.e. the Yolo network detections on the ground truth images. Object detection scores are interesting, since we note that even though the mean IoU computed is similar, the Recurrent Module allows to find an higher number of detections, suggesting that the synthesized frames are more visually similar to the corresponding real ones with respect to the frames generated by the Generative Module.

We validate the realism of the synthesized frames on datasets with color information. We propose to the participants two tracks: in the first one, we propose sequences with a length of 24 frames at 12 fps, while in the second one we show the same sequences but at 24 fps. The generated sequences in the first and in the second tracks were chosen as the most realistic by the 39% and the 42% of the participants, respectively. Interestingly, these close values indicate that the level of detail and color preservation is good, since the time interval for each user to see the synthesized frames influences the final results only in a partial way.

Finally, we conduct also a “fake vs fake” test, in which we ask users to choose the more realistic images between outputs of the Generative and the Recurrent Modules. The 59%
of users indicate the output of the whole framework as the most realistic one.

In Figure 4, we show how $L1$, $Threshold$, $PSNR$, and $SSIM$ metrics vary in relation to the position of the synthesized frame. As expected, the contribution of the Recurrent Module increases along with the length of the sequence, thus confirming the effectiveness of the proposed model.

6. Applications

In a near future in which cameras will be installed in a widespread and massive way, underlying problems such as energy consumption, transmission bandwidth and storage capacity will arise. The adoption of event cameras could mitigate these problems in several application fields. Focusing on automotive applications, for example, the advantages of event cameras when combined with traditional cameras can be significant to reach high frame rates at a limited transmission bandwidth.

Assuming to have an acquisition system equipped with a color and an aligned event camera, the global frame rate $fps$ can be defined as the number of frames (RGB plus event) sent each second. Instead of transmitting only color frames, the replacement of original frames with the corresponding event frame allows to save $S$ bits each second as follows:

$$S = (br_c \cdot fps) - (br_c \cdot fps \cdot (1 - \lambda) + br_e \cdot fps \cdot \lambda)$$ (14)

where $br_c$ and $br_e$ are the bitrates of the RGB and the event camera, respectively, and $\lambda \in [0, 1]$ is the percentage of event data sent in place of color frames.

Considering a RGB camera with a spatial resolution of $128 \times 128$ pixels and a framerate of $25$Hz, coupled with a DVS128 event camera, we can assume an average bitrate of $128 \times 128 \times 3 \times 8 \times 25 \approx 1.23$ Mbps for the former and of $0.29$ Mbps [3] for the latter.

Without taking into account the compression algorithms, which could be applied to both sources of data, the percentage of saved data ranges from $18\%$ with $\lambda = \frac{6}{25}$ to a maximum of $73\%$ when using $\lambda = \frac{24}{25}$. The trade off between the generated image quality and the amount of saved data, i.e. the value of $\lambda$, can be statically or dynamically adapted by hand or an automatic system.

7. Conclusion

In this paper, we have exploited the recently introduced event cameras to develop a framework that is able to synthesize color frames, relying only on an initial or a periodic set of key-frames and a sequence of event frames. The Generative Module produces an intermediate output, while the Recurrent Module refines it, preserving colors and enhancing the temporal coherence.

The capability of the proposed framework has been proved through extensive experiments based on pixel-wise, semantic, and perceptual metrics suggesting that conditional adversarial networks combined with a convolutional LSTM are a promising approach for this task. Moreover, semantic segmentation and object detection scores show the possibility to run traditional vision algorithms relying only on the output of the proposed framework, without the need of rethinking new algorithms and collect new data.
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