A Reproduction of EV-SegNet: Semantic Segmentation for Event-based Cameras

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In 2018, a method was proposed by Iñigo Alonso and Ana C. Murillo for the semantic segmentation of scenes from the DDD17 dataset (DAVIS Driving Dataset). Semantic segmentation (i.e. labelling different types of objects in an image) of street scenes had been a common application for deep neural networks.
So then what was the catch? Whereas traditional methods use camera images as input, EV-SegNet uses event-based data, a datatype that is notoriously unintuitive and hard to interpret for both human and computer brains. As if the challenge was not large enough yet, no existing labeled dataset was available (at the time).
In the context of the 'Reproducibility project' for the Deep Learning course at Delft University of Technology, we attempted to reproduce the results presented in Alonso and Murillo's paper. This blogpost aims to clarify the main concepts from the original paper and presents the reproduction results.

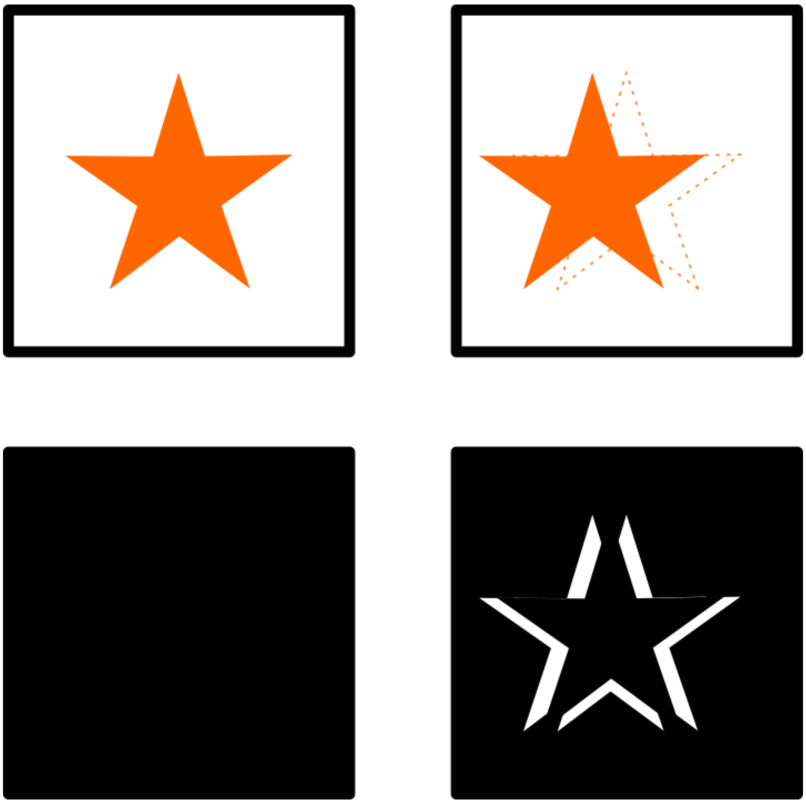
Background Information

In order to make sure that the methodology in the original paper [^1] and reproduction is clear, we will shortly go over some key concepts essential to understanding the process.

Event-based cameras

What are event-based cameras? In contrast to traditional camera sensors, event-based sensors capture, well... events. Simply said: a normal camera captures the intensity of light at a certain location (pixel) on the sensor, the sensor records these intensities at all pixels at once, some interpretation of these values later, we have an image. In any case, the idea is that the photograph contains a snapshot in time of this light intensity data. Event-based sensors, however, only capture changes in intensity at a certain pixel and at a certain time.

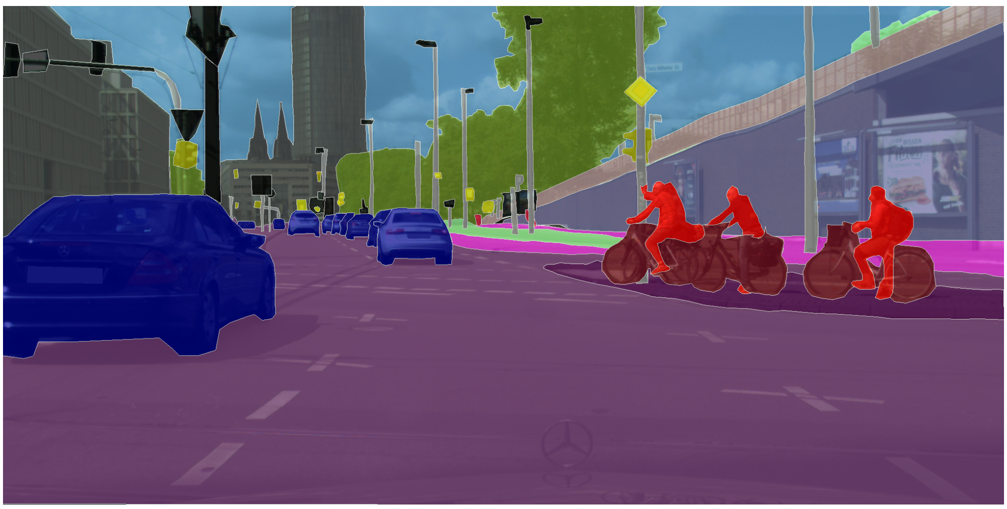
Consider the image below, in the top row we see a representation of a classic camera image: as can be seen, the orange star moves slightly to the left from frame 1 to frame 2, however, based on a single frame we would never know if the star was moving, they are snapshots in time. The bottom row are the event-based representations of the top row: at the first timestep, no changes are noted. At the second step, once the star has moved, some receptors observe a change in intensity.



Important to note is that this representation of event-based images already show a certain interpretation of the event data! In fact, data from event-based cameras can hardly be called an image. The data consists of data points, each containing a timestamp, a location on the sensor, and a measure of the intensity change. Depending on the interpretation of the intensity change, different representations of event-based data can be obtained. This link provides an example of event-based cameras in action.

Semantic (pixel level) image segmentation

Semantic segmentation is the process whereby images are segmented and labeled (through a machine learning process) according to object types/classes that are relevant to the application. In the example below (obtained from the CityScapes Dataset), the classes could be car (blue), cyclist (red) and road (light purple) among others.

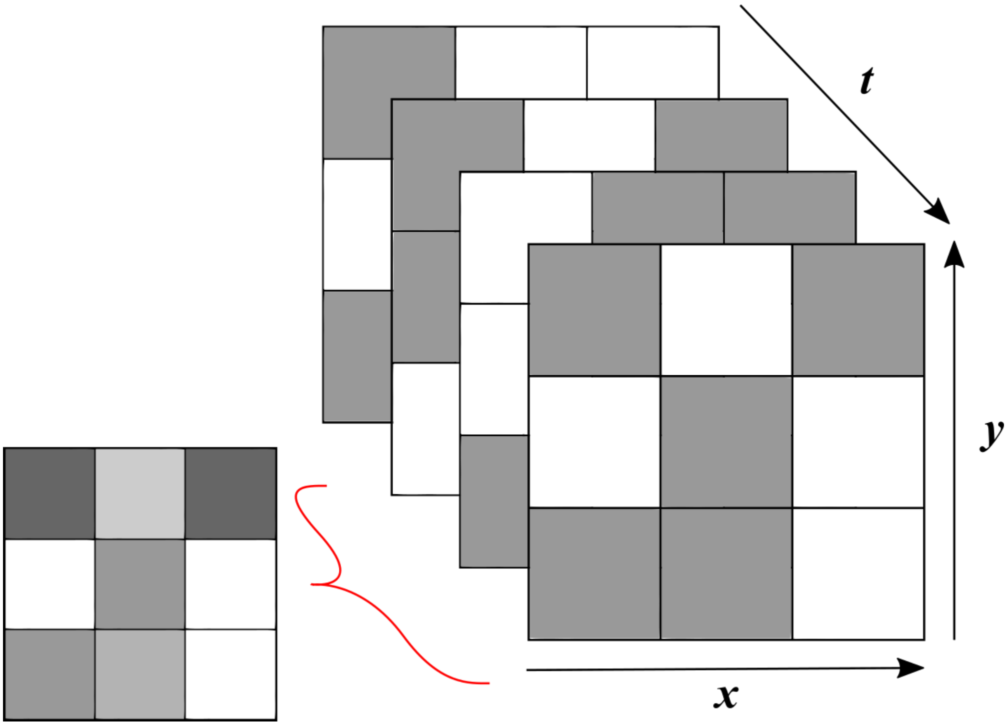


Original method

Event Representation

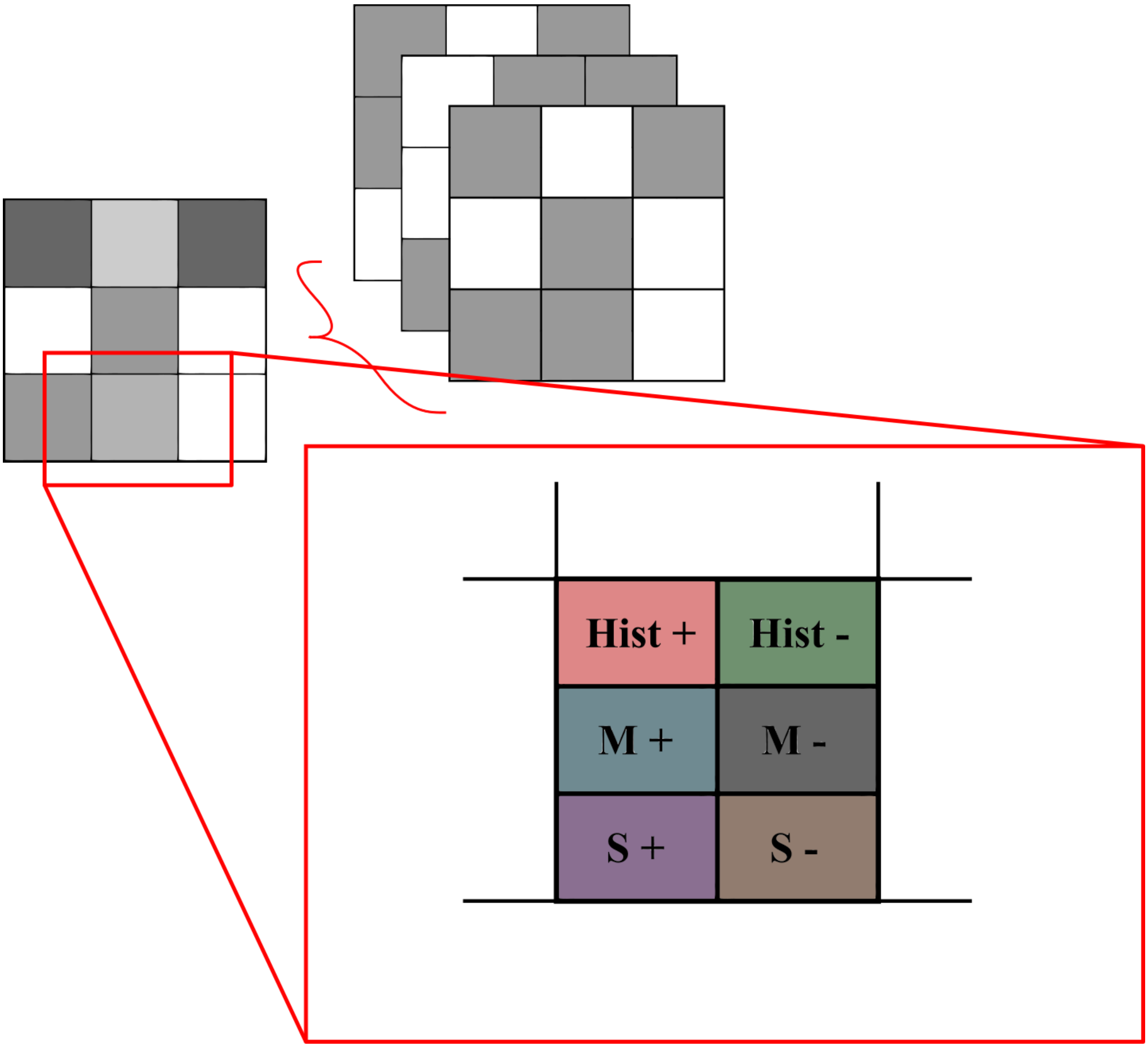
As mentioned, the representation of event data depends heavily on the manner in which it is processed. The most common way to present event data corresponding to a certain time-step t_i as an image is to arrange the data points in an image grid according to the recorded positions x and y, each of these pixels contain information on the events that took place during some time interval containing t_i.

As a reference, this image aims to clarify the concept: A white pixel conveys the absence of a datapoint (i.e. no event was recorded at that time, at that location).

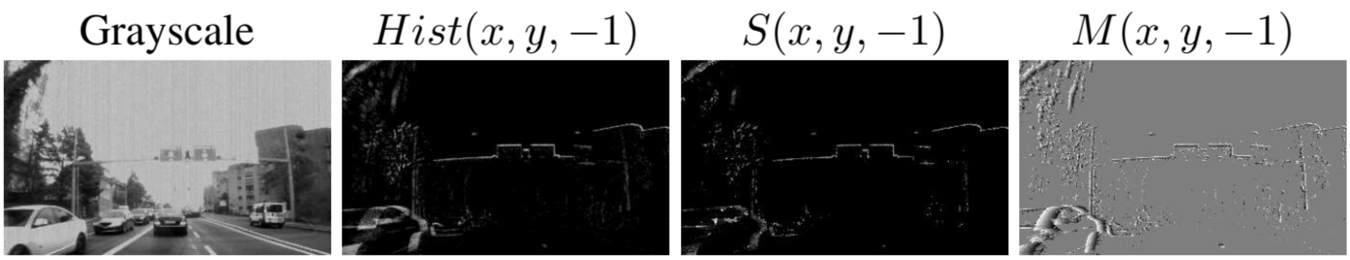


The nature of the information in a pixel varies from method to method, for example one could take the integral of the events in the time interval. Additionally, different kinds of information can be stored in different channels, the same way RGB images' pixels record the intensity of red, green and blue wavelengths. For example, 2 channels can separate positive and negative events.

The method that was proposed stores the event information in 6 channels. The first one is a histogram, it simply accumulates all the magnitudes of the events over the time interval, summing them together. Second is the mean of all events in the time interval and third the standard variation. These three methods all split the information into a positive and a negative channel, resulting in 6 channels.



Please note that the colours in the figure are only meant to signify the various channels, they do not convey actual values, nor are the channels interpreted as colours in the original method. Below an example[^1] of three negative channels can be found.



Ground truth labels

One of the main challenges that Alonso and Murillo faced, was the scarcity of available data. The [DDD17 Dataset]() was one of the few event-based datasets for driving environments. The data contains greyscale images alongside the event-data, however it does not contain ground truth labels.

As to avoid having to generate the label by hand, which is not only time-consuming but can be quite difficult as well, they employed a CNN and trained it on grayscale images from the CityScapes Dataset (that did have ground truths) to generate labels on the greyscale images that accompany the DDD17

event-data. These results had an MIoU score of 83% which they deemed sufficient to serve as ground truths for the event data.

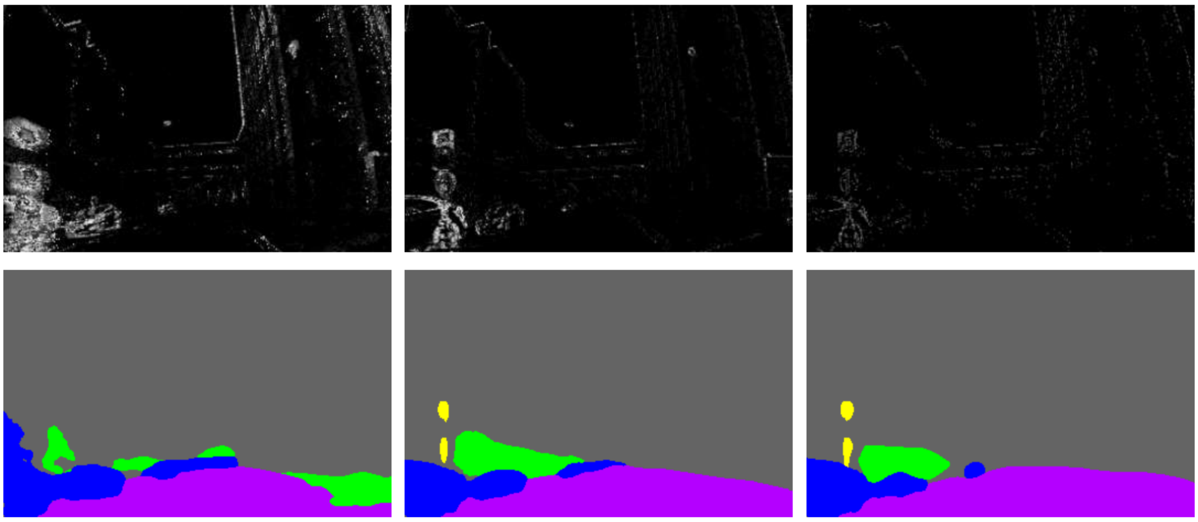
CNN architecture

Since CNN architectures are well known for their good performance on segmentation tasks, the method proposed in the paper employed an architecture heavily inspired on such. The architecture made use of the Xception[^2] model as an encoder and used backpropagation on the per-pixel cross-entropy loss to optimize the model.

Their results

Input	***Accuracy (50ms)***	***MIoU (50ms)***	***Accuracy (10ms)***	***MIoU (10ms***	***Accuracy (250ms)***	***MIoU (250ms)***
Event representation	***89.76***	***54.81***	***86.46***	***45.85***	***87.72***	***47.56***
Grayscale image	***94.67***	***64.98***	***94.67***	***64.98***	***94.67***	***64.98***
Combined	***95.22***	***68.36***	***95.18***	***67.95***	***95.29***	***68.26***

An example of the segmentation result for three different event integration intervals: 10ms, 50ms and 250ms:



Reproduction

The goal of our reproduction[^4] is to attempt to make their method robust for the future: back in 2018, Alonso and Murillo built their method on Python 2.7 and TensorFlow 1.11 structures. We attempted to adapt their code[^3] to be compatible with Python 3.x and TensorFlow 2.7. The model was then trained from scratch, using the data provided with the original paper. Additionally, we checked the performance of the algorithm when provided with newly generated ground truth labels for the testset.

Compatibility

The method that was implemented was using an outdated version of python 2, together with the by now outdated 1.x version of tensorflow. Thus we systematically looked at the outdated functions and methods and converted these to work with tensorflow 2.8 and python 3.x. Most of the changes we made were to the file generating the segmentation labels from the output images, and the file which trains the model. Luckily tensorflow 2.8 contains compatability functions which operate identically to the older functions from tensorflow 1.x.

Using a SOTA SegNet for generating labels

The model used in the original work to generate ground truths has been surpassed by higher accuracy pre-trained models. We elected to use a newer 'pspnet_101' model trained on cityscapes, to see whether the model was somehow very sensitive to intricacies due to the original model used to generate segmentation images. This newer model was trained to generate more than 6 classes, we grouped certain classes together to match the 6 classes used in the paper. The following labels were merged:

- ***road and sidewalk into flat***
- ***building, wall, fence and sky into background***
- ***pole, traffic light and traffic sign into object***
- ***vegetation and terrain into vegetation***
- ***person and rider into human***
- ***car, truck, bus, train, motorcycle and bicycle into vehicle***

Issues with reproduction

Several issues were encountered in the reproduction process which are caused by insufficient information, namely:

- ***The authors did not specify the exact network architecture in the paper, noting only that an Xception encoder is used and that a 'light decoder' is built, "concentrating the heavy computation on the encoder". The repository from the paper's authors includes multiple architectures. The model 'Segception_small' is used by default, but there are reasons to believe why the default in the code is not necessarily the model that was used in the paper, see below.***
- ***The paper references using auxiliary loss during training, this is a common method to combat vanishing gradients in deep models. The '_small' model however does not properly implement an auxiliary loss (in the code it's simply a copy of the normal model loss). Two models in the given repository did properly implement an auxiliary loss, one of which did not use Xception as a base model and hence does not match the paper, the other was so large that our computation resources were insufficient without sacrificing on batch size. We have implemented an auxiliary loss on the '_small' model ourselves and noticed a decrease in performance, see below. We are unsure whether auxiliary loss has actually been used for the results in the paper.***
- ***Not all hyperparameters are fully specified in the paper, most noticeably the exact number of epochs and what type of polynomial scheduling was used. The default number of epochs is 500 in the repository (the paper mentions 30k iterations, which would be around 15 epochs). This adds to the reasons (as above) we have to believe that the defaults in the repository are not necessarily what's been used for the results in the paper.***
- ***The given event data has already been processed, simply supplied as .npy files. The code for the pre-processing steps is not included in the given repository. This means that the time used for differences in the event data (the 50ms, 250ms, ...) in the table above is not fully reproducible***

with supplied code. Although it is given in the paper that the model was trained on event data with integration intervals of 50ms, they also mention that it was tested on 10ms, 50ms and 250ms, but neglect to specify which test data corresponds to which intervals.

- ***The authors are unclear about how they integrated grayscale and event data for the final row in the table above.***
- ***The given 'best' weights in the repository do not actually result in the given results in the paper, the accuracy and mIoU with just inference over those given weights are significantly lower. Refer to the results.***
- ***No learning curves are presented in the paper, only final outcomes. Given that there are some things that are unclear or, having reference learning curves could have helped to see whether we're on the right track with the model used for the results in the paper.***

There were also issues from our side:

- ***Computation resources were limited, which meant we weren't able to use the bigger models in the repository with the given batch size (limited by video memory). Again, we are unsure what model has actually been used as the authors don't provide a detailed description.***
- ***Related to this, we did not manage to get Google Colab to work with the given credits.***

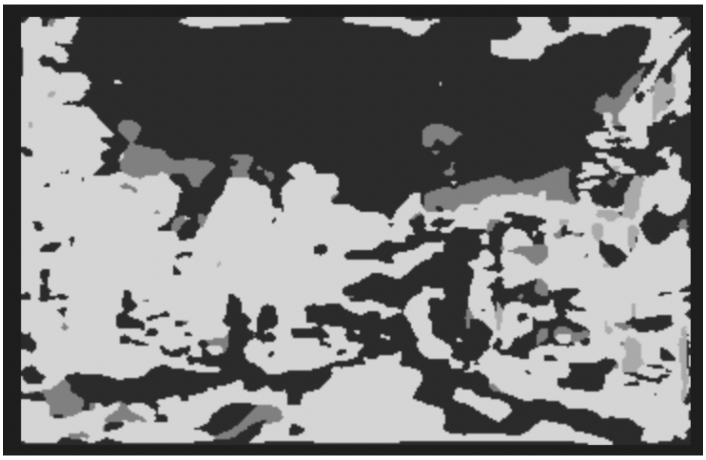
Results

As explained, the codebase has been updated to match up-to-date frameworks and tooling, several other modifications have been made to allow more parameterization, fix several bugs/annoyances and get model storing/saving to work properly. Please review the commit history in the fork [^4] for more info.

We will first present results using the given pre-trained model from the authors. Then present results from our own training with varying amounts of data, and then from our own training with 100% data and a proper auxiliary loss as described in the paper.

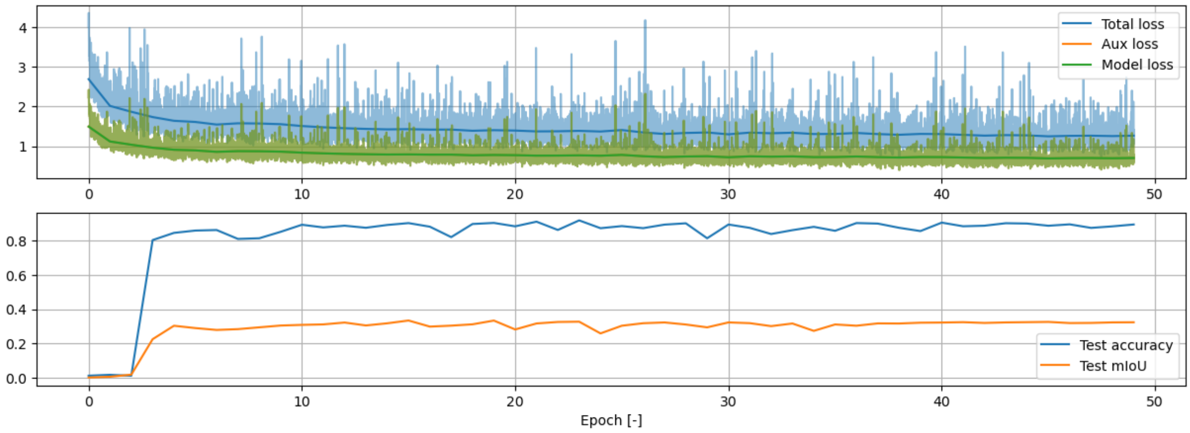
Using the pre-trained model from the authors

Using the pre-trained model in the repository, which the authors state should be able to ' replicate results' [^3] does not get the expected results. On a limited test set of 500 samples, we achieve an accuracy of ~20% and a mean intersection-over-union (mIoU) of under 5%. The resulting segmentation images naturally do not represent the labels at all:

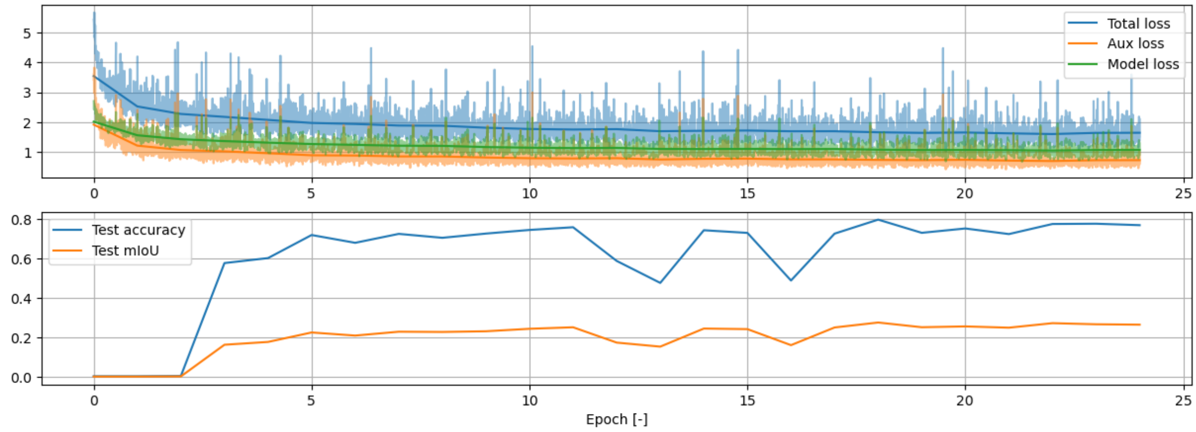


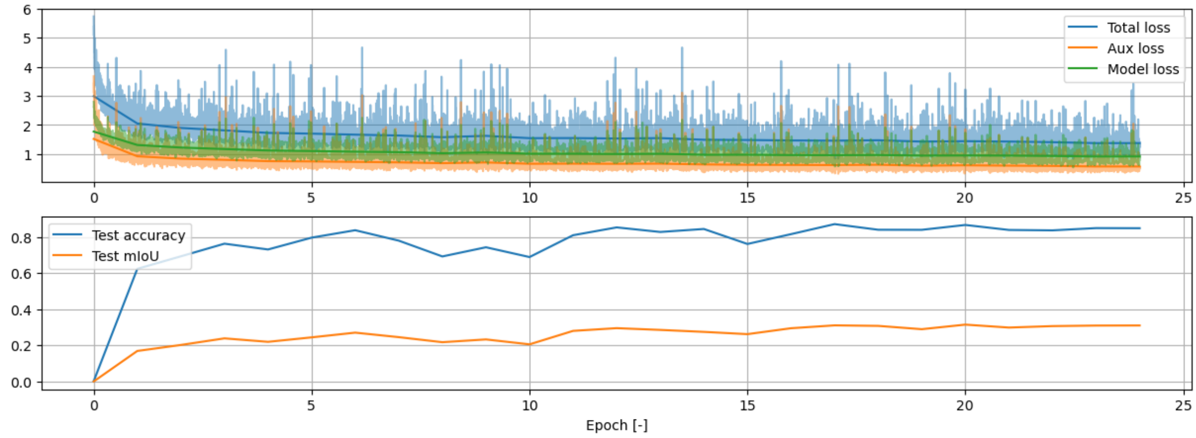
Training the model ourselves with- and without auxiliary loss

At first, we trained the model using the defaults in the repository, this resulted in an accuracy of around 85% and an mIoU of around 30%. This model was trained without auxiliary loss (which, as mentioned, was not implemented in the code base but is mentioned in the paper) and uses 25% of the training samples (500 samples) for 50 epochs (25k iterations), see below loss curves:



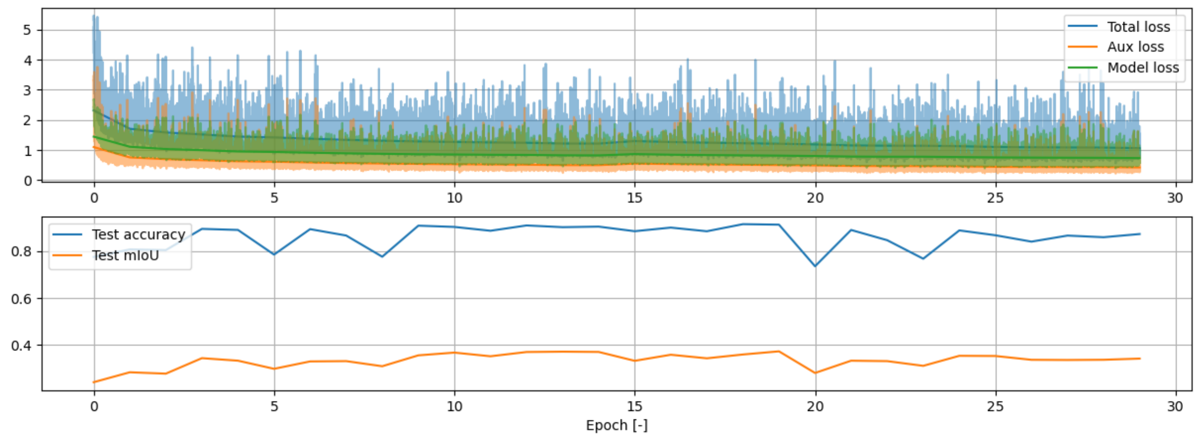
Naturally this model uses less iterations than prescribed in the paper, less training samples and does not use auxiliary loss. We then implemented an auxiliary loss properly and reran training for 25 epochs with 10% and 25% of the training data, to evaluate to what extent adding training samples improved performance. This resulted in the following loss curves for 10% and 25%, respectively:



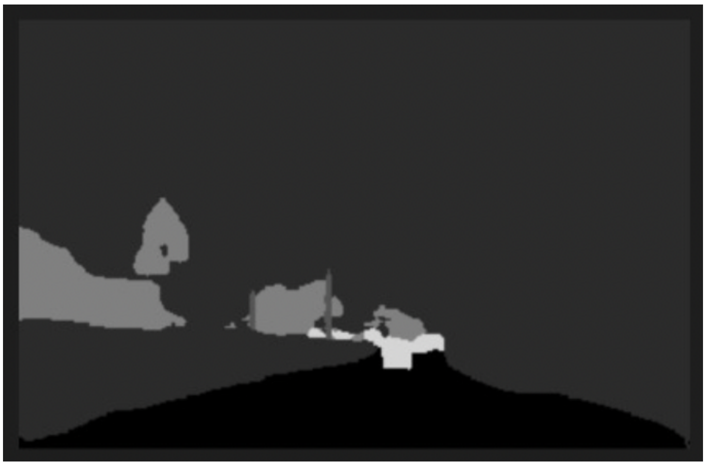


Note that training with 25% of the training samples did result in marginally better test accuracy and mIoU, as well as increased stability during training. Although the accuracies are fairly close to the author's results, the mIoU is significantly lower, this still results in segmentation labels with little value.

Finally, we trained with 100% of the training samples for 30 epochs, so 60k iterations, twice as much as the authors claim in the paper, which resulted in the following loss curves:



Notice that the final performance is only marginally better on the test set than our results for 25% of the training data. One thing we did notice at this point is that the accuracy and mIoU on the training set are increasing as the number of epochs goes up, resulting in segmentation outputs that start to visually resemble the given labels on the training set. The label is the left image, the model output is on the right.



Clearly, then, the fact that we are using the 'segception_small' (because, as mentioned, it is not clear from the paper which of the models is actually used) from the repository is not a large problem as the model is complex enough to start overfitting on the training data. Increasing model complexity might not get us better results on the test set.

Training times

The authors provide no information regarding hardware used for training and the required training time. A single iteration took around 1.1s on an M1 Macbook Pro with Metal acceleration, resulting in training time of around 19 hours for the 60k iterations above.

Reproduction conclusion

In conclusion, we are not able to replicate the results from the authors on multiple fronts:

- ***Inference on the pre-trained weights supplied by the authors does not result in the figures presented in the paper.***
- ***Training the model ourselves does not result in the figures presented in the paper. Even when trying to train for longer than the authors prescribe or adding a proper auxiliary loss as the authors also describe in the paper.***
- ***Event data with different time constants is not supplied, nor is the pre-processing code, hence we simply are not able to replicate these results using this codebase without writing fairly complex event-camera data processing code ourselves. Even in that case, the raw data was not provided by the authors.***

We are unsure where this discrepancy is coming from. The codebase is largely the same, apart from optional changes (i.e. aux loss, less training samples, etc...) or compatibility changes. The dataset is the

same as the author's used as well.

Value of new test labels

As we mentioned before, generating new labels for the testset required merging some predicted labels from the pretrained model. This was easier said than done however: a bit of investigating showed that some 30-ish classes are defined for segmentation tasks for driving scenery. Most applications, including the pretrained model, seem to use only 19 of those, but often neglect documenting which classes exactly. EV-SegNet then was trained to only classify 6 classes, but at least mentions - albeit in passing - the categories (and their subclasses) that were merged into their 6. The challenge was now to identify the 19 classes used by the pretrained model. As it happens, in EV-SegNet's `get_segmentation`[^3] 19 training labels are identified. Validating whether these 19 were in fact also the ones used for the pretrained model was achieved by visual inspection of the generated segmentations. The newly generated and merged 6-class-labels are thus estimates at best.

Also, since we did not have the time to generate new ground truth labels for all 15k training samples (due to our computational limits mentioned above), we only re-labeled the testset. Of course that means that there is a risk of a high disconnect between what the model is trained for and what it is tested on. At most, we can consider the performance on the new test labels as a measure of how robust the method is.

Results on the new test set, do the (poor) results generalize?

We've already seen that the trained model started to overfit on the training data and that we achieved comparably poor results on the testing data (around 30% mIoU), with the limited number of testing labels that we did generate, we are getting similar mIoU values.

Given our inability to properly reproduce results from the paper and the amount of time we spent trying various things on the given dataset, we did not have time to do this properly, including training on new ground truths (see above). The value of these results has also gone down now that we are unable to get good results at all.

Formalities

This reproduction was performed in the context of Delft University of Technology's course on Deep Learning (CS4240, 2022 Q3). Our team consisted of three members: Rafaël Beckers, Evert De Vroey and Roy Vorster.

Both Rafaël and Roy were mainly responsible for the technical aspects of this reproduction: adapting the original code to be compatible with modern methods. In addition, Rafaël investigated options to harvest Google Colab's computational resources and Evert was responsible for generating the new labels from a pretrained model. Both Evert and Roy were responsible for communicating the results, namely writing this blogpost.

References

[^1]: Iñigo Alonso and Ana C. Murillo. Ev-segnet: Semantic segmentation for event-based cameras. 2018. URL: https://arxiv.org/abs/1811.12039

[^2]: F. Chollet. Xception: Deep learning with depthwise separable convolutions. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 1800–1807, 2017.

[^3]: Iñigo Alonso and Ana C. Murillo. EV-SegNet Repository

*[^4]: Roy Vorster. Reproduction EV-SegNet Repository*_