Improving FlowCube's re-identification performance with GAN data augmentation - Extended Abstract

August 8, 2022

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ABSTRACT In this study, we introduce FlowCube™, a camera-based traffic sensor that measures bicycle, vehicle and pedestrian trips in a privacy-safe manner. To achieve this, FlowCube uses a model chain consisting of object detection, local tracking, trip filtering and re-identification (re-id). Whereas FlowCube's performance is fit-for-purpose during the daytime, it degrades in more challenging nighttime conditions. With that, this study is aimed at improving FlowCube's night-time re-id performance. To that end, since the poor nighttime re-id performance is thought to be due to a lack of nighttime re-id training data, GAN (AU-GAN) data augmentation with alpha blending is proposed to enrich FlowCube's re-id training data with synthetic nighttime imagery. In addition to measuring the impact on the nighttime re-id performance, we investigated how this augmentation affects FlowCube's general re-id performance. The findings show that this method improves FlowCube's mean re-id F1 scores and reduces the variance between results across multiple training runs, both for nighttime and general re-id. With that, we have demonstrated AU-GAN data augmentation with alpha blending to be beneficial for improving FlowCube's nighttime and general re-id performance. The code for this project is not publicly available as it is property of Technolution.

Keywords: data augmentation, generative adversarial networks, classification, alpha blending, re-identification.

1 INTRODUCTION

1.1 Context

Today, about 55% of the world's population lives in cities, and by the year 2050 this percentage is said to increase to about 70% [1]. Needless to say, such a grand amount of people will result in an abundance of commute which, if not managed correctly, can lead to problematic traffic scenarios. And so, as the population grows, the infrastructure has to keep up. That is, pedestrian, cyclist and vehicle traffic has to be managed in an efficient manner that minimizes congestion. Doing this has a positive effect on time, cost and the environmental aspects. However, the problem that arises is a lack of measurement data on vehicle, pedestrian and cyclist traffic flows, e.g. traffic throughput, routes and travel time. Therefore, it is hard to identify the problematic areas. This is where FlowCube™ comes in.

1.2 FlowCube

FlowCube is a camera-based traffic sensor that can measure bicycle, vehicle and pedestrian trips between sensors in a privacy-safe manner. To achieve this, FlowCube uses a model chain consisting of object detection, local tracking, trip filtering and re-id. Here, object detection and re-id models are trained on an in-house dataset that is created with the use of pseudo-labeling.

1.3 Problem statement

Whereas FlowCube is fit-for-purpose in daylight conditions, its performance degrades in more challenging lighting conditions. Focusing on the re-id part of FlowCube, most notably, this disparity in performance can be attributed to a lack of nighttime imagery in the pseudo-labeled re-id training dataset. With that, the nighttime re-id training data is limited.

1.4 Goal

In this work, we address FlowCube's current re-id limitations in the nighttime setting and propose an improvement, i.e. Generative Adversarial Network (GAN) data augmentation. More specifically, AU-GAN [2] is used to augment FlowCube's re-id training set with synthetic nighttime imagery. In addition, we investigate how this augmentation affects FlowCube's overall re-id performance.

2 METHOD

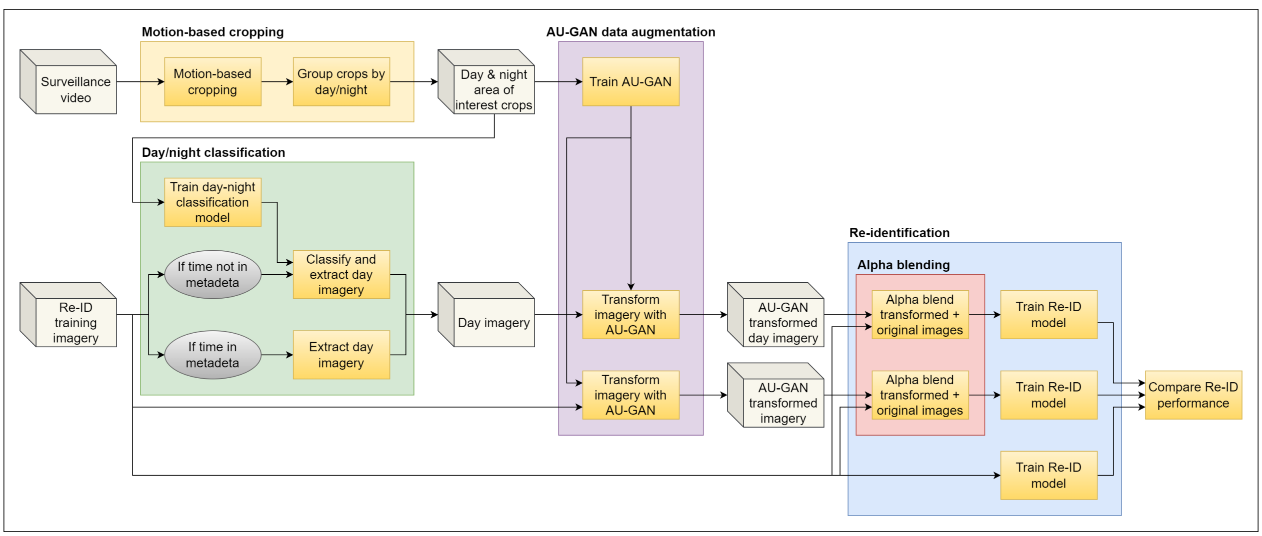

Figure 1: A high level overview of the proposed methodology.

2.1 Motion-based cropping

As can be seen in Figure 1, our method added four new components to the existing re-id model. First, we developed a custom made motion based cropping algorithm. This, as the pseudo-labeling algorithm wasn't able to generate sufficient amount of nighttime training imagery, and AU-GAN's input imagery requirements were lower, i.e. it doesn't require tracklets, but merely example imagery from the day- and nighttime domain. The algorithm used frame differencing to highlight all moving objects in a scene. Then, K-means clustering with a (high) fixed K was used to identify clusters of movement. Afterwards, agglomerative clustering with a distance threshold was used to merge clusters that described the same object. This resulted in a newly formed dataset of daytime and nighttime imagery which could be used to train AU-GAN.

2.2 Day/night classification

For this research, the two different augmentations were tested, i.e. day-to-night, and day-to-night + night-to-night (image-to-night) AU-GAN transformed imagery, affected the re-id performance. However, the timestamps were not available for all images in the re-id training dataset. Thus, we used a classification (LeNet [3]) model to access the time of day.

2.3 AU-GAN data augmentation

An AU-GAN day-to-night (D2N) and image-to-night (I2N) transformed equivalent version of the original re-id training dataset was then constructed.

2.4 Alpha blending

With the original and two AU-GAN transformed datasets we could train the re-id model on the 'original + D2N augmented' or 'original + AU-GAN I2N' datasets. However, rather than using the raw imagery from both datasets, we used an alpha blend between the original and AU-GAN transformed imagery during re-id image loading in the training step. Alpha blending takes two images and blends them together with a ratio $\alpha \in [0, 1]$, that specifies the transparency (1 - α) and opaqueness (α) of the two images respectively, as can be seen in equation 1).

$$I_{blend} = (1 - \alpha) \cdot I_1 + \alpha \cdot I_2 \tag{1}$$

, where I denotes an image and α is applied random uniformly, i.e. $\alpha \leq \alpha_{max} \in [0, 1]$.

3 RESULTS AND DISCUSSION

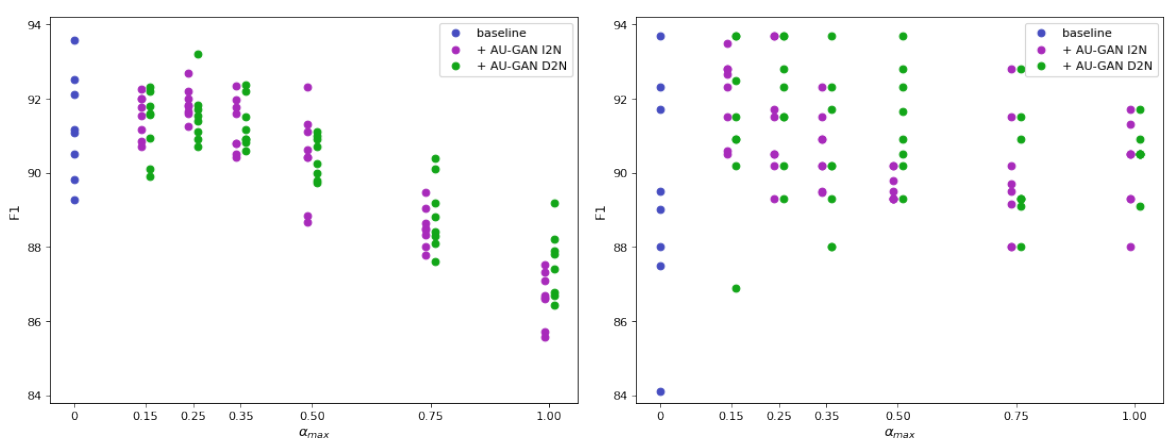

Figure 2: The day-to-night (D2N) and image-to-night (I2N) re-id F1 scores on the FlowCube's validation dataset (left) and a subset of FlowCube's validation set containing only its nighttime imagery (right), trained with varying values for α_{max}.

In Figure 2, we see that, for low values for α_{max}, both the day-to-night and image-to-night AU-GAN augmentation improved the average re-id F1 scores and reduced the variance in between runs, both in terms of general re-id and nighttime re-id. And although the single highest general re-id score was always produced by the baseline model, this does not imply superiority over the proposed method. This, as machine learning is of a stochastic nature. The baseline's high variance in between runs illustrates its uncertainty, but this uncertainty also causes it to sometimes (accidentally) derive optimal patterns. However, average results describe a more telling picture of the model's actual performance.

4 CONCLUSION

With that, we can state that the AU-GAN augmentation, combined with an alpha blend, can positively affect both FlowCube's general and nighttime re-id performance. These finding imply that the AU-GAN augmentation with alpha blend offers a rich set of key augmentations, such as color adjustment and added noise, that are useful for improving the task of re-id (when applied in a low magnitude, i.e. with $\alpha_{max} \in [0.25, 0.35]$).

ACKNOWLEDGEMENT

I would like to thank both my daily and VU supervisors Michael Dubbeldam and Arnoud Visser for assisting me throughout this project and offering me valuable feedback, and also Technolution for providing me with the equipment required to execute my research.

REFERENCES

[1] The World Bank. Urban Development, 2020.

[2] Jeong-gi Kwak, Youngsaeng Jin, Yuanming Li, Dongsik Yoon, Donghyeon Kim, Hanseok Ko. Adverse weather image translation with asymmetric and uncertainty-aware gan, 2021.

[3] Yann LeCun, Yoshua Bengio, Leon Bottou, Patrick Haffner. Gradient-based learning applied to document recognition, 1998.