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Image Enhancement using GANs for Monocular Visual Odometry

Jon Zubieta Ansorregi

*Ikerlan Technology Research Centre,
Basque Research and Technology Alliance (BRTA)
Arrasate/Mondragón, Spain.
jonzubieta76@gmail.com*

Maidier Zamalloa Akizu

*Ikerlan Technology Research Centre,
Basque Research and Technology Alliance (BRTA)
Arrasate/Mondragón, Spain.
mzamalloa@ikerlan.es*

Mikel Etxeberria Garcia

*Ikerlan Technology Research Centre,
Basque Research and Technology Alliance (BRTA)
Arrasate/Mondragón, Spain.
mikel.etxeberria@ikerlan.es*

Nestor Arana Arexolaleiba

*Electronic and Computer Science
Mondragon Unibertsitatea
Arrasate/Mondragón, Spain.
Department of Materials and Production
Aalborg Universitet
Aalborg, Denmark.
narana@mondragon.edu*

Abstract—Drones, mobile robots, and autonomous vehicles use Visual Odometry (VO) to move around complex environments. ORB-SLAM or deep learning-based approaches like DF-VO are two of the state-of-the-art technics for monocular VO. Those two technics perform correctly in outdoor scenarios but show some limitations in indoor environments. The extreme lighting conditions, non-Lambertian surfaces, or occlusion of indoor environments can disturb the visual information, and so the odometry information. Generative Adversarial Network (GAN) architectures recently proposed in the literature can help overcome image low-light and blurring limitations. This research study aims to assess image enhancement's impact using GANS on the Visual Odometry algorithm DF-VO. Since DF-VO is also based on visual geometric information, the paper first considers the effect of three different GAN architectures in the camera's calibration. Then, the impact in the odometry information computed by DF-VO is evaluated. The preliminary results show that the reprojection error and the uncertainty of the calibration of a pin-hole-based camera do not increase significantly, and DF-VO's performance is improved.

Index Terms—Image enhancement, Calibration, Visual Odometry, Deep Learning

I. INTRODUCTION

Autonomous vehicles such as Robots, Car and Trains are equipped with multiple sensors. Inertial Measurement Unit (IMU), Laser Imaging Detection and Ranging (LiDAR), Global Positioning System (GPS), Wheel Odometry or Visual sensor are some of them. Visual sensors like RGB or RGB-Depth (RGBD) cameras in a mono or stereo setting are extensively studied since they offer rich information, which helps understand the vehicle's surrounding environment.

For example, YOLO detector can be used to detect traffic sign from visual information [1]. UNet is a well-known network that performs images semantic segmentation [2]. The visual segmentation allows us to understand the meaning of

each pixel. Finally, Visual Odometry (VO) or Simultaneous Localization and Mapping (SLAM) are approaches that compute the vehicle's movement using images and SLAM, in addition to the motion to create a map and localize itself in the map [3]. In all those problems, Deep Neural Network concepts and tools are becoming a popular approach.

They are based on the ideas that crucial features available in the information can learn if there is enough information and a learning guideline if offered (i.e. ground truth or a loss function). However, there is not always enough information available. Night driving [4], driving in changing weather condition [5], underground railway [6], mining [7], or indoor parking [8] are some scenarios where researchers are studying how to take advantage of various types of visual sensors to compute odometry. Those scenarios are characterized by low lighting conditions like the mine tunnel or changing lighting when the train goes from the tunnel and enters the platform. We can also find specular surfaces [8], and the images are usually blurring due to poor light conditions.

Another issue in the scenarios mentioned above is the difficulty of collecting the necessary images dataset [9] to train the neural network. Some researchers try to train the neural network using augmented data. The data quantity can be increased using traditional data augmentation techniques such as pixel colour operations, blurring using kernel filters, edge enhancement, rotation, cropping or translation. It can also be augmented using Generative Adversarial Networks (GANs) [10]. Other researchers try to enhance the images before using the pre-trained network [11] is trained for image recorded in good conditions, and there is no enough data to train the network with new images. In both cases, GANs seem to be a promising solution.

This research aims to study to which extend GANs can

improve the monocular Visual Odometry results by enhancing low lighting and blurring images. More precisely, the effect of image enhancement using GANs on image geometrical properties will be studied.

II. RELATED WORKS

A. Visual Odometry (VO)

Visual Odometry (VO) refers to using data from cameras to estimate the camera's position changes over time. We refer to monocular VO when one single camera is used to capture frames. VO is used in robotics and autonomous vehicles to calculate the robot's position displacement. Depending on the method, different monocular VO approaches can be defined. *Geometric VO* approaches rely on image geometric characteristics and perspective camera model to reconstruct ego-motion between consecutive images. One of the most standard geometric VO approaches is called ORB-SLAM2 [12] and has become the state-of-the-art comparison for all the later approaches. It is based on feature matching consecutive frames and on bundle adjustment algorithm.

Geometric monocular VO suffers from scale drift issue where scale is inconsistent and expensive global bundle adjustment algorithms are applied to refine the camera's pose. Furthermore, monocular VO algorithms have a depth-translation scale ambiguity issue.

With the improvements of Deep Learning-based Computer Vision techniques, Deep Learning in VO has started using extensively. It has led to *DL-based VO* algorithms that can solve some of these problems. Some are considered *hybrid VO* algorithms within these DL-based approaches as they mix geometric characteristics and DL-based inference.

In this context, Zhan *et al.* proposed the unsupervised VO algorithm DF-VO [13]. This algorithm is a hybrid approach that uses both geometric image information and deep learning-based depth and flow estimation to estimate the camera pose.

B. Data enhancement

Generative Adversarial Networks (GAN). GAN networks are a type of machine learning models designed by Ian Goodfellow and his teammates in 2014 [14]. Their functioning consists of two neural networks competing with each other during their training. One network is known as the generator, and it aims to generate data capable of fooling the second network, which is the discriminator. At the same time, the discriminator must determine whether the generated data is real or fake. Through this competition, both networks keep improving until the generators capability to create realistic data becomes acceptable. Once the training is done, the discriminator is no longer used, and the generator is the one that works, generating new data.

The main challenges identified in the scenarios mentioned above are poor or lousy lightning conditions and blurring on captured images. So two different GAN variations have been chosen: *EnlightenGAN* and *DeblurGAN*.

DeblurGAN. The task of image deblurring is to get the sharp version of the blurred image corrupted by some unknown

blur kernel or spacially variant kernel. *DeblurGAN* [15] proposed the solution based on a conditional GAN and content loss for its learning. It achieves state-of-the-art performance in terms of structural similarity measure and visual appearance. Besides, it is 5 times faster than the closest competitor, "Deep Deblur" [16].

EnlightenGAN. Images captured in lousy light conditions suffer from low contrast, poor visibility and high ISO noise. Those issues challenge computer vision algorithms. The proposed solution by *EnlightenGAN* [17] is an effective unsupervised generative adversarial network.

The hypothesis stated in this work proposes that the mentioned GANs may improve hybrid-VO (geometric+deep learning) approaches performance in low-lighting scenarios. The research will study first the effect of using GANs in geometric visual information using a calibration process. And then the results of the DF-VO in low-lighting trajectories with and without enhancing images using GANs.

III. EXPERIMENTATION

The state-of-the-art monocular VO algorithms are based on minimizing the reprojection error of consecutive image frames. The reprojection error is estimated by solving the essential matrix encoding the epipolar geometry and assuming the camera satisfies the pinhole camera model. To evaluate the GAN based data enhancement architectures applicability in VO algorithms, it becomes essential to analyze the impact of GAN based data enhancement techniques in the camera parameters by following a camera calibration procedure

Therefore, to assess the applicability of GAN-based image enhancement techniques in the VO algorithm such as DF-VO, first, its impact on the camera calibration's reprojection error will be performed.

A. Calibration experimentation

This experimentation has aimed to evaluate the impact that the used image enhancement techniques have on the reprojection error and uncertainty during the camera calibration. The calibration has been done using Matlab's calibration tool *Camera Calibrator*.

1) *Calibration setup:* Firstly, two primary datasets have been generated named *Day-calibration* and *Night-calibration*. The dataset *Day-calibration* consists of images captured on appropriate lighting conditions. On the other hand, the dataset *Night-calibration* is composed of the same images in the *Day-calibration* dataset but with poor light conditions. For that, the setup in 1 has been used, with a camera and a calibration pattern. The calibration pattern was placed in different poses inside of the visual area of the camera. In each pose, two images have been taken: One with the light of the room switched on and the second with the light turned off, simulating poor lighting conditions.

Once these two primary datasets have been created, two datasets have been derived from them. *DeblurGAN* has been applied to the *Day-calibration* dataset to create *DB-calibration*

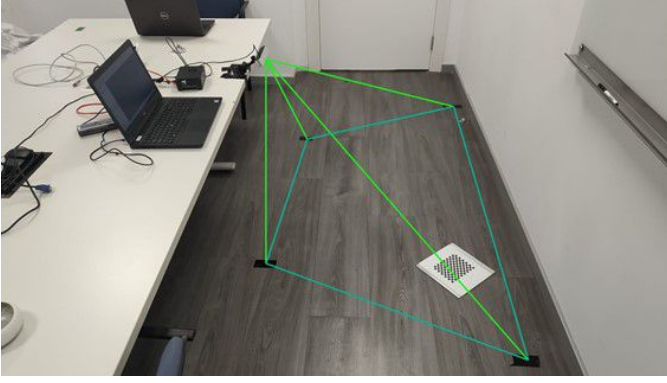


Fig. 1: Setup used to generate day-calibration and night-calibration datasets.

dataset, and *EnlightenGAN* has been applied to the *Night-calibration* dataset to get *Enlighten-calibration* dataset. In 2 can be seen the scheme of the datasets used for calibration.

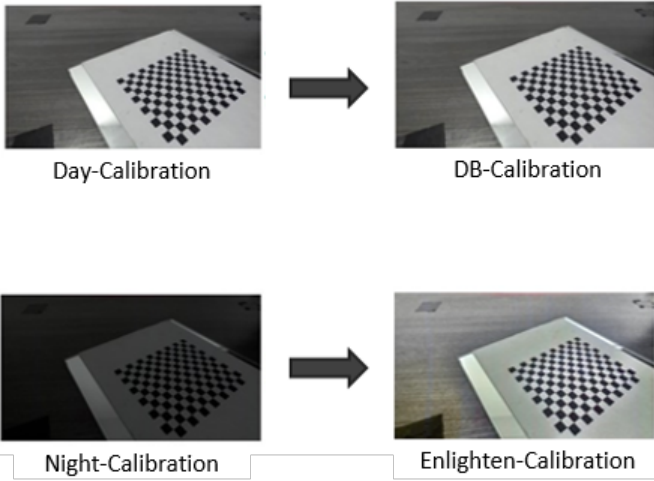


Fig. 2: Distribution of the datasets used in the dataset experimentation.

2) *Calibration evaluation metrics*: To evaluate the calibration results, the following metrics have been used:

Mean reprojection error: Provides a qualitative measure of accuracy during calibration. A reprojection error is a distance between a pattern keypoint detected in an image used in calibration and a corresponding world point projected into the same image.

$$ReprojError_{mean} := \frac{1}{n+m} \sum_{i=1}^n \sum_{j=1}^m (K P_{ij} \vec{p}_i - \vec{x}_{ij})^2 \quad (1)$$

where K are the camera intrinsic parameters, P_j is the camera pose, $\vec{p}_{ij}$ are feature locations in 3D and $\vec{x}_{ij}$ its projection in a 2D image plane.

Uncertainty: It can be said that the result of a measurement is an approximation of the measured value. Therefore, to

have a more realistic estimate, it is necessary to know its uncertainty.

Both the reprojection error and the uncertainty have been calculated with Matlab's calibration tool.

3) *Calibration results*: The following tables I and II represent the calibration results through the previously mentioned mean reprojection error and uncertainty and the camera parameters, the focal length and the principal points.

Metric	Day-calibration	DB-calibration
Mean reprojection error	0.1089	0.1208
Focal length	690.31; 689.58	690.34; 689.42
Principal point	644.96; 381.21	644.76; 380.90
Radial distortion	0.014; -0.013	0.01; -0.01
Focal length uncertainty	4.171; 4.104	4.837; 4.76
Principal point uncertainty	0.546; 2.367	0.637; 2.73
Radial distortion uncertainty	0.002; 0.002	0.002; 0.002

TABLE I: Day calibration results.

As shown in Table I, the focal length and principal point in both *Day-calibration* and *DB-calibration* are similar. However, the *Mean reprojection error* and the *Uncertainty* increase slightly.

Metric	Night-calibration	Enlighten-calibration
Mean reprojection error	0.0775	0.0904
Focal length	694.058; 693.605	693.379; 692.858
Principal point	645.006; 380.768	644.871; 380.984
Radial distortion	0.015; -0.017	0.015; -0.017
Focal length uncertainty	2.558; 2.482	3.204; 3.130
Princ. point uncertainty	0.351; 1.490	0.435; 1.840
Radial dist. uncertainty	0.001; 0.001	0.001; 0.002

TABLE II: Night calibration results.

In Table II can be seen that the focal length and principal point in both *Night-calibration* and *Enlighten-calibration* are also similar, being the the mean reprojection error and uncertainties a bit higher in *Enlighten-calibration*.

The first sets of experiments show that *DeblurGAN*, and *EnlightenGAN* degrades the reprojection error and the uncertainty of the calibration parameters, that is, to the geometrical information available in the images slightly. However, geometrical information is not the only information used by the latest VO techniques. So, in the next section, the effect of image enhancement in VO will be studied.

B. Visual Odometry experimentation

1) *VO setup*: To evaluate the previously mentioned Data Enhancement techniques in VO algorithms, the need for a dataset with specific characteristics (i.e., consisting of dark photos or well illuminated, but with improvable sharpness) raised. Usually, VO algorithms are evaluated on standard datasets, such as KITTI [18]. After researching on most used datasets for VO evaluation [19], no standard dataset with adverse lighting conditions was identified in the autonomous vehicle sector. This led us to generate our database by making recordings of the same trajectory during day and night.

For that, two closed paths were chosen, where the starting and the arrival point are the same, as this strategy allowed the

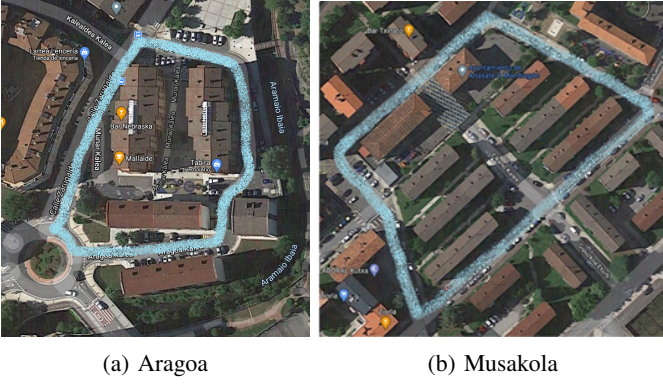


Fig. 3: Trajectories used to generate the VO experimentation dataset using a camera installed in a car.

generation of the reference data using a state-of-the-art VO algorithm ORB-SLAM2 [12] that uses loop closure to relocalize the camera. Two distinct trajectories have been chosen to increase the robustness of the results and conclusions obtained from experimentation. The trajectories shown in figure 3 have been named after the street where they are located: Aragoa and Musakola.

The camera used to record the dataset is a ZED Stereo Camera. The images' resolution is 1280x720 pixels at 60fps (120 Hz) with an electronic synchronized rolling shutter, automatic gain and a lens aperture of F2.0. As it can be seen in Figure 4, the camera has been placed on the upper part of the front window of the car, thus preventing the front of the vehicle from invading the lower part of the recording.



Fig. 4: Camera setup for the recordings of the generated dataset.

Two sequences were recorded in each trajectory. One of the sequences has been recorded during the day and one at night. The sequences recorded during the day have been used to generate other sequences using the data enhancement technique mentioned above: *DeblurGAN*. The sequences recorded at night were used to create another sequences using *EnlightenGAN* data enhancement approach. Consequently, 8 sequences were generated finally, four for each trajectory: two original sequences and two enhanced sequences. The full gathered dataset is depicted in Table III.

2) *VO evaluation metrics*: The evaluation of the generated enhanced datasets in DF-VO algorithm has been done using common metrics from standard datasets. Absolute Trajectory Error (ATE) is used where the root-mean-square error between estimated trajectory poses and the respective reference is calculated. For that, both trajectories are aligned through a transformation S using Horns [20] method. Given this transformation, the absolute trajectory error matrix at time i

Trajectory	Sequence	Frames	Characteristic
Aragoa	00	1150	Recorded at daylight in Aragoa
	01	1150	Sequence 00 with <i>DeblurGAN</i>
	02	1400	Recorded at night in Aragoa
	03	1400	Sequence 03 with <i>EnlightenGAN</i>
Musakola	04	1640	Recorded at daylight in Musakola
	05	1640	Sequence 05 with <i>DeblurGAN</i>
	06	1480	Recorded at night in Musakola
	07	1480	Sequence 08 with <i>EnlightenGAN</i>

TABLE III: Full generated dataset for experimentation. The datasets contain 8 sequences, 4 from each trajectory.

is calculated as

$$E_i := Q_i^{-1} S P_i \quad (2)$$

where P_i and Q_i are the estimated pose and ground truth pose at time, respectively. Then the root-mean-square (RMSE) over all i is calculated:

$$ATE = \left(\frac{1}{n} \sum_{i=1}^n \|trans(E_i)\|^2 \right)^{\frac{1}{2}} \quad (3)$$

For VO relative evaluation, relative pose error (RPE) and average translational error (t_{err}) are also common metrics. The RPE measures the drift error per frame of the trajectory [21]. Relative pose error matrix at time step i is defined as:

$$E_i := (Q_i^{-1} Q_{i+1})^{-1} (P_i^{-1} P_{i+1}) \quad (4)$$

where P_i and Q_i are the estimated pose and ground truth pose at time i , respectively. The total number of relative poses from a sequence with n camera poses can be calculated a $m = n - 1$. Then, the RMSE is calculated as in the previous metric:

$$RPE = \left(\frac{1}{m} \sum_{i=1}^m \|trans(E_i)\|^2 \right)^{\frac{1}{2}} \quad (5)$$

Following the evaluation criteria proposed in the KITTI evaluation benchmark, average translational error $t_{err}(\%)$ is used on sub-sequences of different lengths. The error is calculated in the same way as RPE. But instead of calculating the relative error from frame to frame over all the sequence, the average error for all possible sub-sequences along $\{100, \dots, 800\}$ m is used. The relative error matrix is calculated as in 4. Then, RMSE over all sub-sequences RPE is calculated.

3) *VO results*: As shown in Table IV, in the Aragoa trajectory, on the sequences recorded at day, the minimum ATE was obtained in the 01 sequence (enhanced using *DeblurringGAN*) 18.36m, slightly lower than the original 00 sequence.

On the night sequences, ATE over a 300m run from the 02 sequence obtained was 36.21m. However, the enhanced (*EnlightenGAN*) sequence 03 has an ATE of 28.40m. Therefore, the *EnlightenGAN* enhancement algorithm has improved the results obtained in the original sequence by 7.81m.

Trajectory	Sequence	ATE (m)	ATE (%)	RPE (m)	RPE (%)
Aragoa 300m	00	18.36	6.12	0.26	0.78
	01	19.55	6.51	0.26	0.78
	02	36.21	12.07	0.25	0.49
	03	28.40	9.46	0.24	0.49
Musakola 450m	04	15.43	3.42	0.31	0.39
	05	15.70	3.48	0.31	0.39
	06	50.78	11.73	0.35	0.46
	07	40.78	9.06	0.35	0.46

TABLE IV: Results obtained from DF-VO application in the generated dataset where Absolute Trajectory Error (ATE) and Relative Pose Error (RPE) are measured.

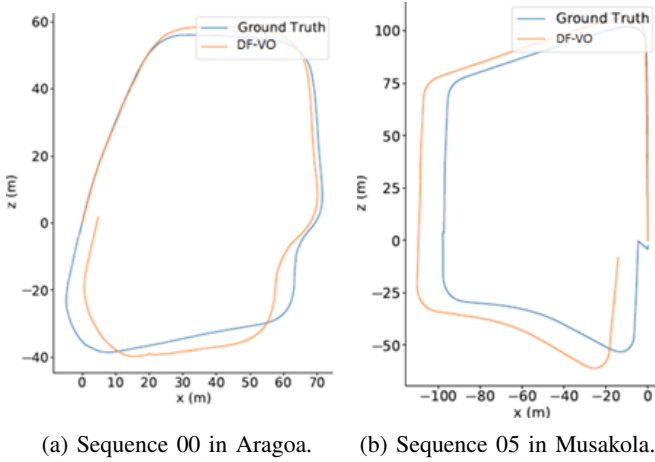


Fig. 5: Sample comparison between DF-VO estimation and the reference created by ORB-SLAM2.

In the Musakola trajectory, the results in terms of ATE are similar to those of Aragoa. The dataset generated by the *DeblurGAN* algorithm have accumulated an ATE similar to the original 04 sequence. In the dataset generated by the *EnlightenGAN* (sequence 07), the ATE has been 12m lower than its source dataset Musakola night (sequence 06).

On the other hand, the relative errors (using RPE metric) were almost identical between the original dataset and its derivatives in both the Musakola and Aragoa trajectories. These results can also be seen on sample trajectories in Figure 5, where the reference created using state-of-the-art ORB-SLAM2 and the result obtained with DF-VO are compared.

IV. CONCLUSIONS

In this paper, the application of GAN based image enhancement architectures in an unsupervised monocular visual odometry algorithm called DF-VO is evaluated. The evaluated GAN techniques *DeblurGAN* and *EnlightenGAN*, aim to enhance the image's blurring and lighting conditions. The images captured by a camera installed in an autonomous vehicle (car, train, tram), being a moving element, may include low-light and blurring that can disturb the visual information.

State-of-the-art monocular VO algorithms are based on minimizing the reprojection error of consecutive frames captured by the camera. The error is estimated by solving the essential

matrix, which depends on the intrinsic camera parameters, and assuming the camera satisfies the pinhole camera model. In this study, the enhanced images calibration procedure is pursued to assess the three GAN architecture's effect in the camera's calibration. The experimental results show that the analyzed GAN architectures do not disturb the camera calibration parameters significantly. The reprojection error and the uncertainty of the camera's intrinsic parameters (optical centre and focal length) being slightly worse are still aligned with the optimal calibration parameters provided by the manufacturer. Therefore, the experimental calibration results support GAN-based enhancement architectures in unsupervised monocular VO algorithms.

The selected visual odometry algorithm for GAN based enhancement architectures evaluation is DF-VO. DF-VO is an unsupervised hybrid visual odometry algorithm based on deep learning and geometric properties. A proprietary database containing the characteristics required by the GAN architectures (low-light, blurring and improvable sharpness) was created by a monocular camera installed in a car. Two close-loop car routes were defined, and the same routes with daylight and nightlight were recorded.

The experimental results show *EnlightenGAN* architectures improve the DF-VO performance in low-light scenarios, as *EnlightenGAN* increases the number of characteristics points used by DF-VO even if image uncertainty is slightly worse in the enhanced images. The ATE value decreases in Aragoa route from 12.07 to 9.46, and it reduces from 11.73 to 9.06 in the route Musakola. The performance obtained by *DeblurGAN*'s architecture is more limited. The experimental results observed a similar performance when evaluating the DF-VO algorithm in daylight enhanced images. Note these results support the conclusion obtained in the images' calibration procedure enhanced by the GAN architectures.

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