Chapter 1

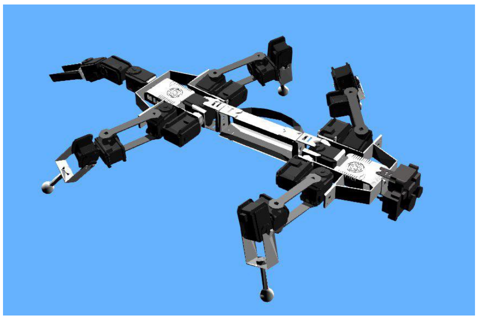
Implementation

This sections talks in detail about the implementation of the framework. We will first talk about from the utilized robot, then describe each step in the dataset generation, illustrate the utilized estimators and finish by listing the employed software.

1.1 Robot

We tested our framewotk on a a legged crocodile robot called *Krock* developed at EPFL. The next figure shows the robot in real life with a cloat and in a simulated enviroment.

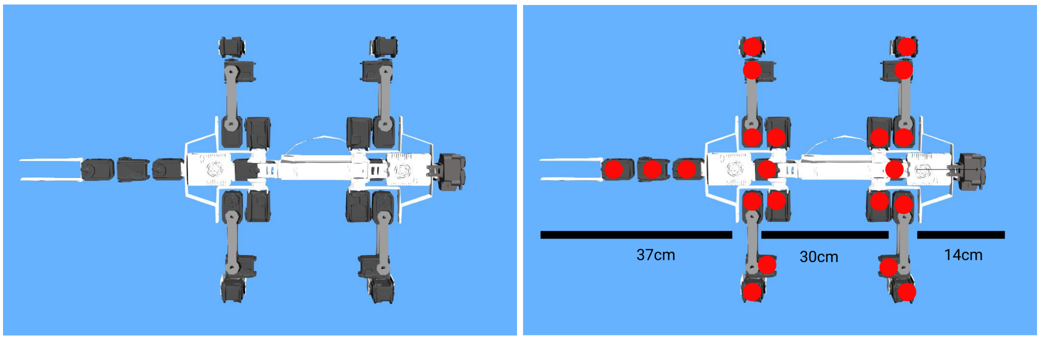
(a) Krock in real life.



(b) Krock in the simulator.

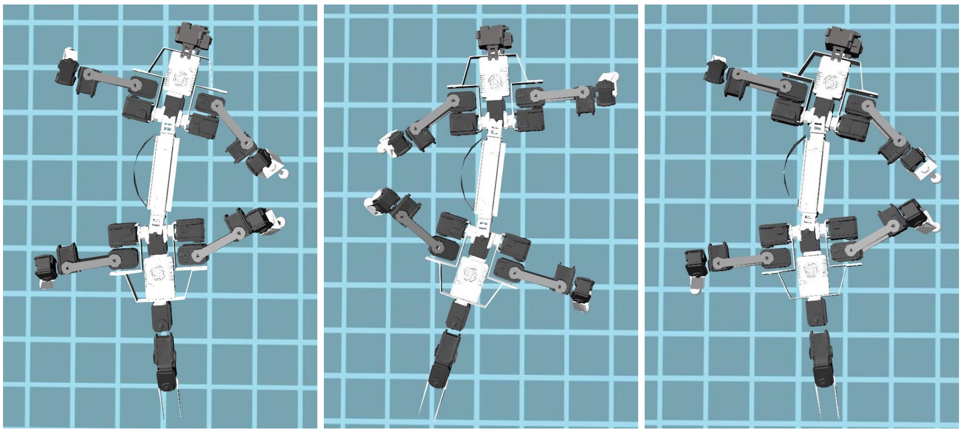
Figure 1.1. *Krock*

Krock has four legs, each one of them is equipped with three motors in order to rotate in each axis. The robot can raise itself in three different configurations, gaits, using the four motors on the body connected to the legs. In addition, there are another set of two motors in the inner body part to increase Krock's move set. The tail is composed by another set of three motors and can be used to perform a wide array of tasks. The robot is $85cm$ long and weights around $1.4kg$. The next figure **??** shows *Krock* from the top helping the reader understanding its composition and the correct ratio between its parts. Also, each motor is highlighted with a red marker. *Krock*'s moves by lifting and



(a) Top view of *Krock* (b) Details highlighted in *Krock*

moving forward one leg after the other. The following figure shows the robots going forward. In



(a) $t = 1$ (b) $t = 2$ (c) $t = 3$

Figure 1.3. *Krock* moving forward.

our framework we fixed the gait configuration to normal, showed in figure **??**, where the body is at the same legs' motors height.

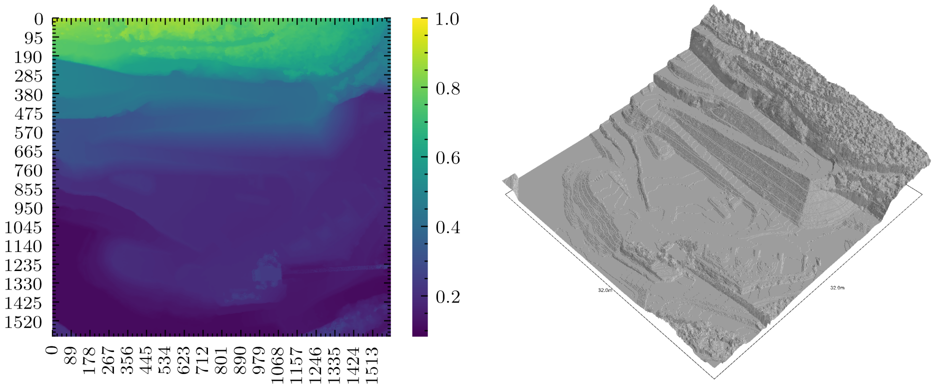
Add Krock gait picture

1.2 Data Gathering

To train a traversability estimator we need a dataset. This section describe in detail how to create, collect and process the data gather from a simulated enviroment to generate a dataset we can use to perform supervised learning.

1.2.1 Heightmap generation

To collect the data throught simulation we first need to generate meaningful terrain to be explored by the robot. Each map is stored as heightmap, a 2D array, an image, where each pixel's value represents the terrain height. For example, the following image shows an heightmap representing a real world quarry and the relative terrain. We created thirty maps of 513×513 pixel with a resolution



(a) Heightmap. (b) 3D rendered

Figure 1.4. This image shows an heightmap and the 3D render of a quarry.

of $0.02cm/pixel$ in order to represent a $10 \times 10m$ terrain using 2D simplex noise **?**. Simplex noise is a variant of Perlin noise **?**, a widely used technique in the terrain generation litterature. We divide the maps into five main categories of terrains to cluster differents ground features: $bumps$, $rails$, $steps$, $slopes$/$ramps$ and $holes$. For some map we add three different rocky texture to create more complicated situations, all the maps configuration are shown in detail in table **??**.

Bumps: We genered four different maps with increasing bumps' height using simplex noise with features size $\in [200, 100, 50, 25]$.

Bars: In these maps there are wall with different shapes and heights. In

Rails: Flat grounds with slots.

Steps: These are maps with various steps at increasing distance and frequency.

Slopes/Ramps: Maps composed by uneven terrain scaled by different height factors from 3 to 5 used to include samples where *Krock* has to climb.

Holes We also included a map with holes

1.2.2 Simulator

We used Webots to move *Krock* on the genereted terrain. The robot controlled was implemented by EPFL and handed to IDSIA . The controller implements a ROS' node to publish *Krock* status including its pose at a rate of $250hz$. We decide to reduce it to $50hz$ by using ROS build it `throttle` command. To load the map into the simulator, we fist had to convert it to Webots's

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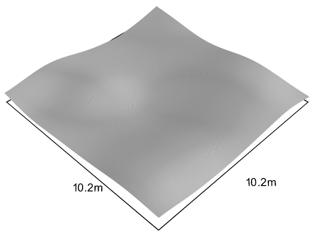
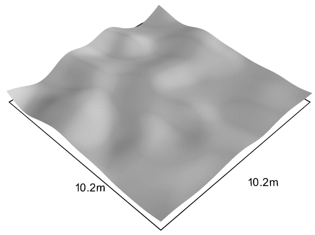
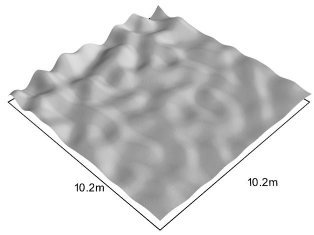


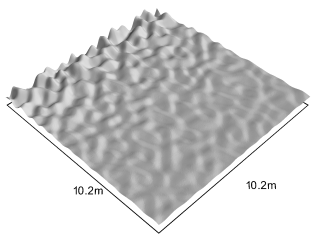
(a) *bumps0*



(b) *bumps1*

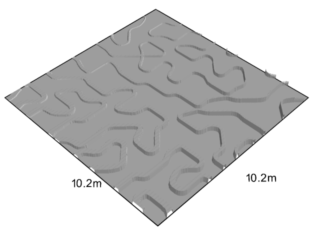


(c) *bumps2*

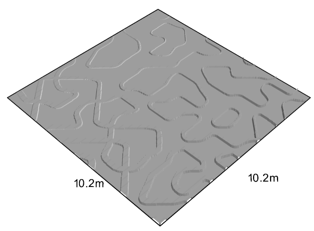


(d) *bumps3*

Figure 1.5. Bumps maps (10×10m).

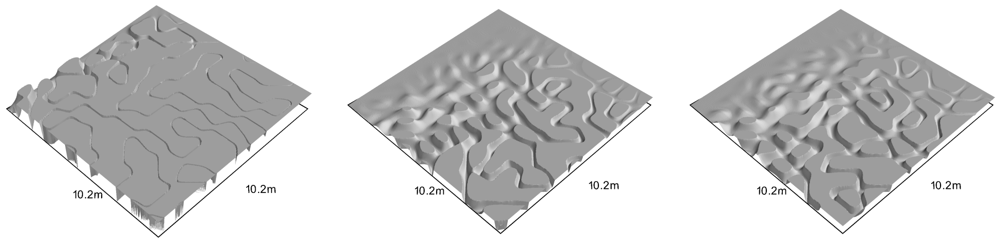


(a) *bars1*



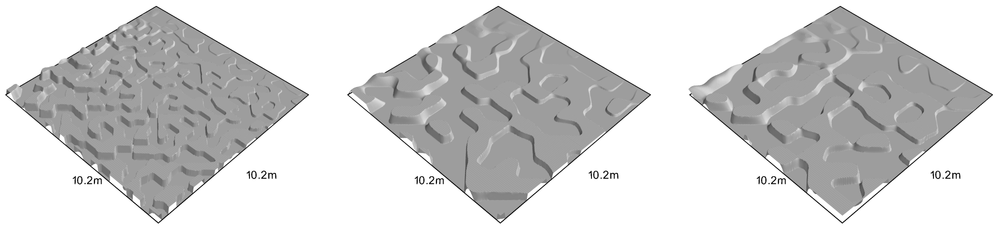
(b) *bars3*

Figure 1.6. Bars maps (10×10m).



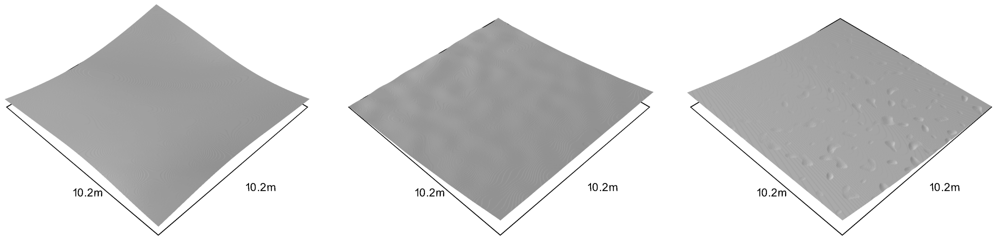
(a) *rails1* (b) *rails2* (c) *rails3*

Figure 1.7. Rails maps (10×10m).



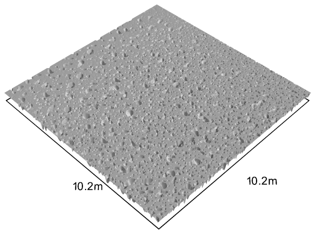
(a) *steps1* (b) *steps2* (c) *steps3*

Figure 1.8. Steps maps (10×10m).



(a) *ramp0* (b) *ramp1* (c) *slope_rocks1*

Figure 1.9. Slopes maps (10×10m).



(a) *holes1*

Figure 1.10. Holes map (10×10m).

.wbt file. Unfortunately, the simulator lacks support for heightmaps so we had to use a script to read the image and perform the conversion.

To communicate with the simulator, Webots exposes a wide number of ROS services, similar to HTTP endpoints, with which we can communicate. The client can use the services to get the value of a field of a Webots' Node, for example, if we want to get the terrain height, we have to ask for the field value `height` from `TERRAIN` node. In addition, to call one service, we first have to get the correct type of message we wish to send and then we can call it. We decided to implement a little library called `webots2ros` to hide all the complexity needed to fetch a field value from a node.

We also implement one additional library called `Agent` to create reusable robot's interfaces independent from the simulator. The package supports callbacks that can be attached to each agent adding additional features such as storing its interaction. Finally, we used *Gym* **?**, a toolkit to develop and evaluate reinforcement learning algorithms, to define our environment. Due to the library's popularity, the code can easily be shared with other researches or we may directly experiment with already made RL algorithm in the future without changing the underlying infrastructure.

1.2.3 Real world maps

To later evaluate the model's performance, we decide to use real world terrain. We gather two heightmaps produced by ground mapping flying drones from sensefly's dataset, a quarry and a small village. Figure 1.11 shows the original and a 3D render of the heightmap for each terrain

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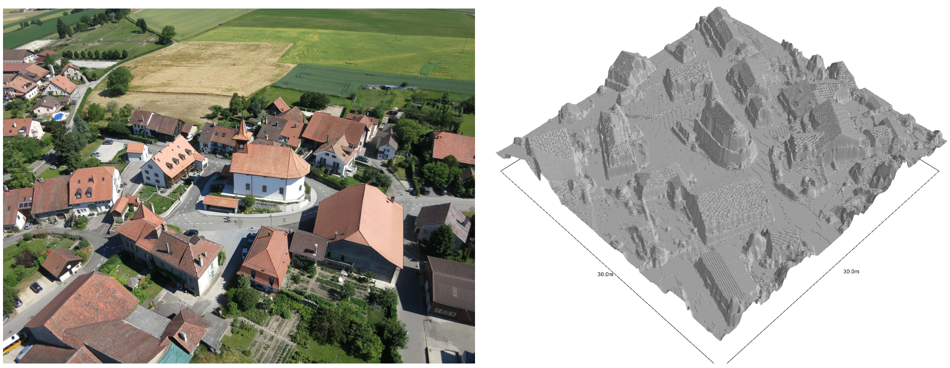
1.3 Simulation

To collect *Krock*'s interaction with the environment, we spawn the robot on the ground and let it move forward for t seconds. We repeat this process n times per each map. Unfortunately, spawning the robot is not a trivial task. In certain maps, for instance, *bars1*, a map with tons of walls, we must avoid spawning Krock on an obstacle otherwise the run will be ruined by *Krock* getting stuck at the beginning introducing noise in the dataset. To solve the problem, we defined two spawn strategies, a random spawn and a flat ground spawn strategy. The first one is used in most of the maps without big obstacles such as *slope_rocks*. This stragety just spawn the robot on random

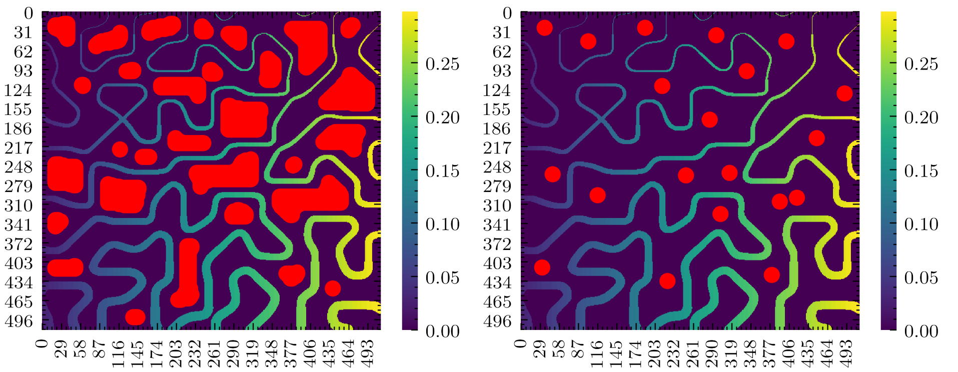
(a) Quarry



(b) A small village.

Figure 1.11. Real world maps obtained from sensefly's dataset. The left images shows the real world location while on the right a render in 3D of the coresponding heightmaps. Booth images have a maximum height of 10m.

position and rotation. While, the flat ground strategy isfirst selects suitable spawn positions by using a sliding window on the heightmap of size equal Krock's footprint and check if the mean pixel value is lower than a small threshold. If so, we store the center coordinates of the patch as a candidate spawing point. Intuitively, if a patch is flat then its mean value will be close to zero. Since there may be more flat spawing positions than simulations needed, we have to reduce the size of the candidate points. To maintaing the correct distribution on the map to avoid spawing the robot always in the same cloud of points, we used K-Means with k clusters where k is equal to the number of simulations we wish to run. By clustering, we guarantee to cover all region of the map removing any bias. The following picture shows this strategy on *bars1*. The following table shows



(a) Flat regions (b) K-Means with $k = 20$

Figure 1.12. Examples of the spawning selection process (marked as red blobs) for the map *bars1*

the maps configuration used in the simulator.

1.4 Postprocessing

After the run Krock on each map, we need to extract the patches for each stored pose p_i and compute the advancement for a given time window, Δt.

1.4.1 Parse stored data

First, we turn each *.bag* file into a pandas dataframe and cache them into *.csv* files. We used `rosbag_pandas`, an open source library we ported to python3, to perform the conversion. Then, we load the dataframes with the respective heightmaps and start the data cleaning process. We remove the rows corresponding tp the first second of the simulation time to account for the robot spawning time. Then we eliminate all the entries where the *Krock* pose was near the edges of a map, we used a threshold of 22 pixels since we notice *Krock* getting stuck in the borders of the terrain during a simulation. After cleaning the data, we convert *Krock*quaternion rotation to Euler notation using the `tf` package from ROS. Then, we extract the $\sin$ and $\cos$ from the Euler orientation last component and store them in a column. Before caching again the resulting dataframes into *.csv* files, we convert the robot's position into heightmap's coordinates that are used later to crop the correct region of the map.

Map	Height(m)	Spawn	Texture	Simulations	max time(s)
bumps0	2	random	- rocks1 rocks2	50	10
bumps1	1	random	- rocks1 rocks2	50	10
bumps2	1 2	random	- rocks1 rocks2 -	50	10
bumps3	1	random	- rocks1 rocks2	50	10
steps1	1	random	-	50	10
steps2	1	flat	-	50	10
steps3	1	random	-	50	10
rails1	1	flat	-	50	20
rails2	1		flat	-	10
rails3	1		flat	-	10
bars1	1 2	flat	- -	50	10
bars3	1	flat	-		
ramp0	1	random	rocks1 rocks2	50 50	10
ramp1	3 4 5	random	-	50	10
slope_rocks1	3 4 5	random	-	50	10
holes1	1	random	-	50	10
quarry	10	random	-	50	10
		Total: 1600			

Table 1.1. Maps configuration used in the simulator.

To compute the robot's advancement in a time window Δt we look for each stored pose ,p_t, in the future, $p_{t+\Delta t}$, and see how far it went. This is describe by the following equation:

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The correct value of Δt is crucial. We want a time window small enough to avoid smoothing to much the advancement and making obstacle traversale, and big enough to include the full legs motion. We empirically set $\Delta t = 2$ since it allows Krock to move both its legs and does not flat the advancement too much.

1.4.2 Extract patches

Each patch must contain both Krock's footprint, to include the situations where the obstacle is under the robot, and certain amount of ground region in front of it. Intuitively, we want to include in each patch the correct amount of future informations according to the selected time window. Thus, we should add the maximum possible ground that Krock could traverse.

To find out the correct value, we must compute the maximum advancement on a flat ground for the Δt and use it to calculate the final size of the patch. We compute it by running some simulations of *Krock* on flat ground and averaging the advancement getting a value of 71cm in our $\Delta t = 2$s.

Each patch must include Krock's footprint and the maximum possible distance it can travel is a Δt. So, since Krock's pose was stored from IMU located in the juncture between the head and the legs, we have to crop from behind its length, 85cm minus the offset between the IMU and the head, 14cm. Then, we have to take 71cm, the maximum advancement with a $\Delta t = 2$s plus the removed offset. The following figure visualizes the patch extraction process. Lastly, we create a final dataframe containing the map coordinates, the advancement, and the patches paths for each simulation and store them to disk as *.csv* files.

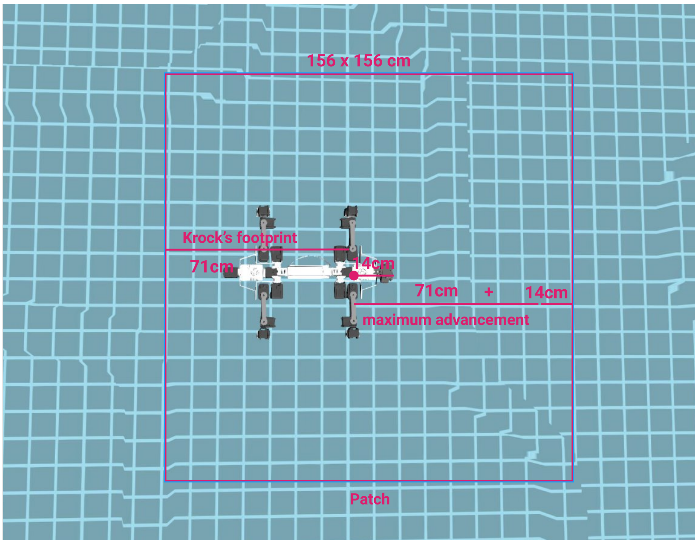
The whole pipeline takes less than one hour to run the first time with 16 threads, and, once it is cached, less than fifteen minutes to extract all the patches. In total, we created almost half a milion images.

Once we extract the patches, we can always re-compute the advancement without re-running the whole pipeline. The next figure show the proposed pipeline. The following figure shows the mean advancement across all the maps used to train the model in a range of ± 0.70cm, the maximum advancment the used time window, $\Delta t = 2$s. As sanity check, we visualized some of the patches from the train set ordered by advancement, to conclude the data generation process was correct. Tigure 1.16 shows a sample of fourty patches. All the handles used to postprocess the data are available as a python package. Also, we create an easy to use API called `pipeline` to define a cascade stream of function that is applied one after the other using a multi-thread queue to speed-up the process.

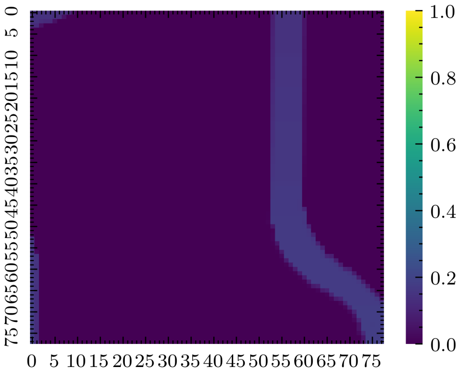
1.4.3 Label patches

To decide whether a patch is traversable or not traversable we need to decide a *threshold*, tr, such as if a patches has an advancement major than tr it is label as traversable and viceversa. Formally, a patch p_i is label as *not traversable* if the advancement in a given time window $\Delta t = 2$ is less than the threshold $tr_{\Delta t = n}$

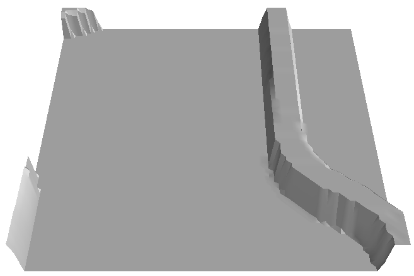
Ideally, the threshold should small enough to include as less as possible false positive and big enough to cover all the cases where Krock gets stuck. We empirically compute the threshold's value by spawing Krock in front of a bumps and a ramp and let it walk.



(a) Robot in the simulator.



(b) Cropped patch in 2d.



(c) Cropped patch in 3d.

Figure 1.13. Patch extraction process for $\Delta t = 2$s.

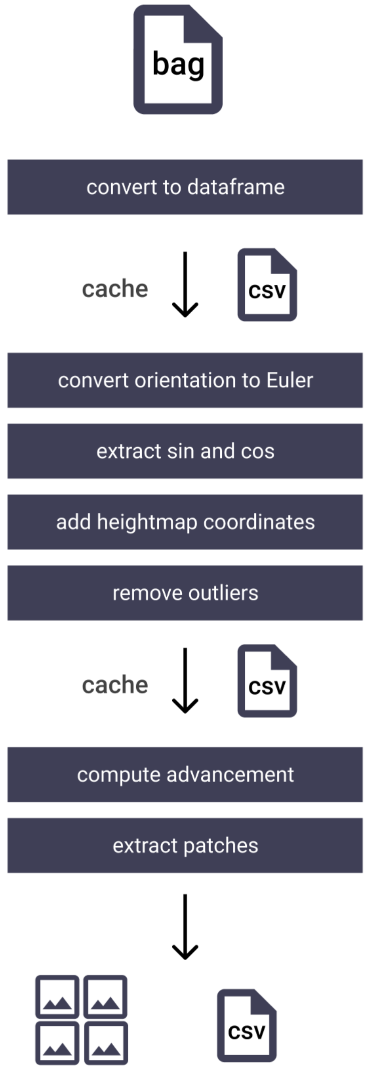


Figure 1.14. Postprocessing Pipeline flow graph, starting from the top.

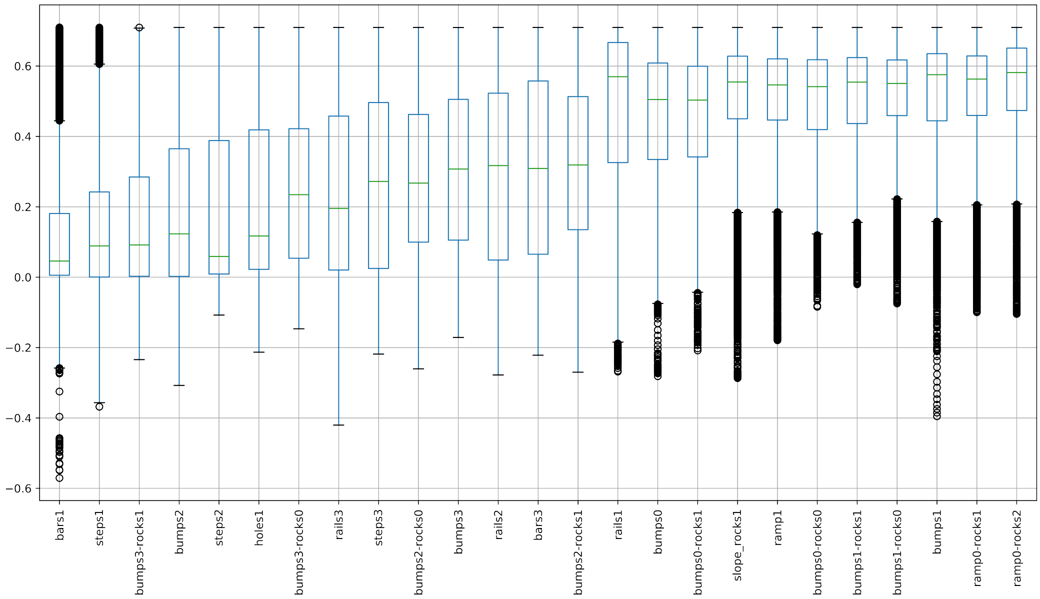


Figure 1.15. Advancement on each map with a $\Delta t = 2$s in ascendent order.

Bumps We spawned the robot on the *bumps3* map close to the end and let it go for 20 seconds. Figure **??** shows Krock in the simulated environment.

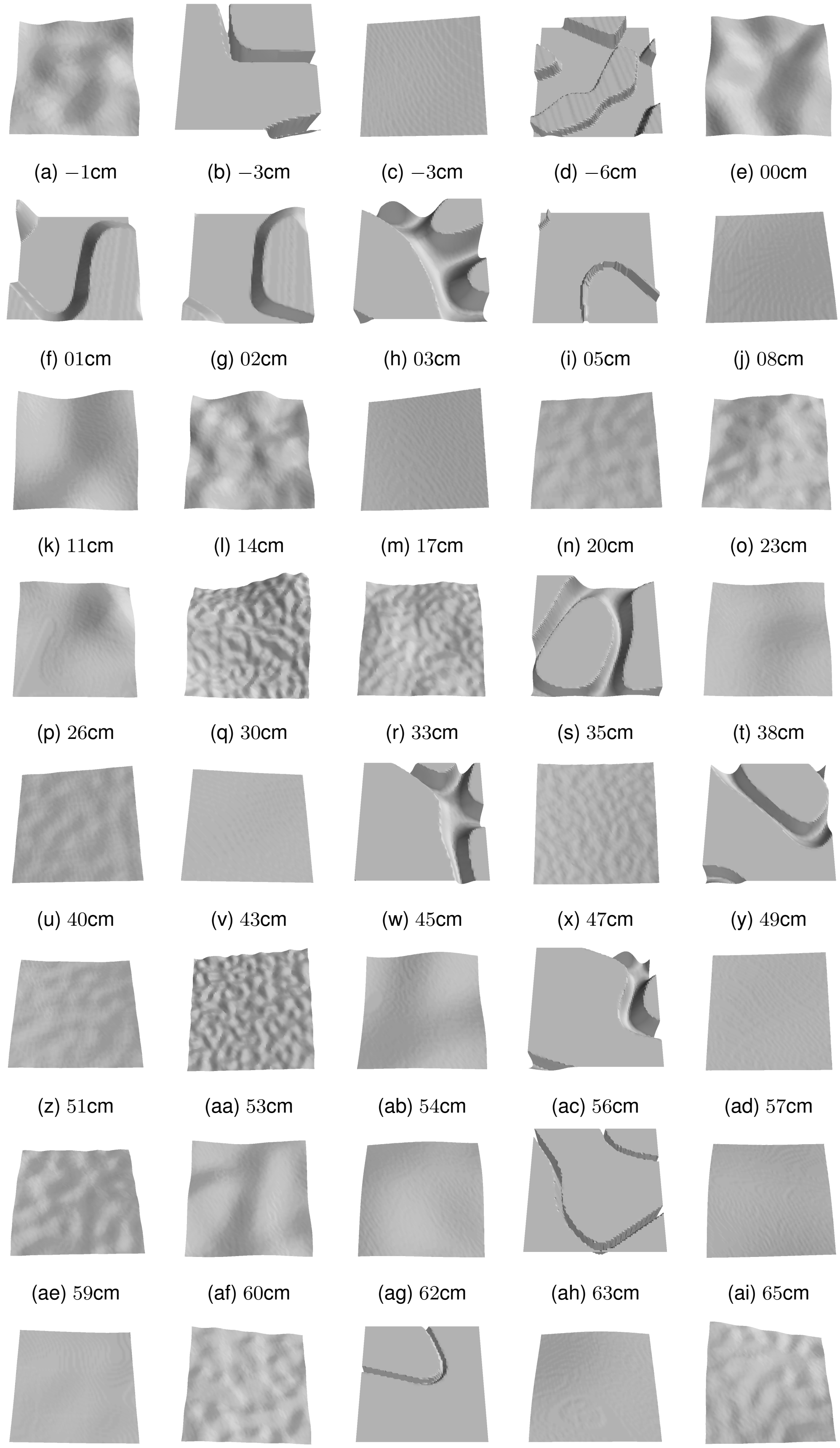
Due to its characteristic locomotion, Krock tries to overcome the obstacle using its legs to move itself to the top but it fell backs producing a spicky advancement where first it is positive and then negative. Figure 1.18 shows the advancemnet on this map with $\Delta t = 2$, we can notice the noisy output.

A wheel robot, on the other hand, will not produce such graph since it cannot free itself easily from an obstacle. Image a wheel robot moving forward, once it hits an obstance it stops moving, if we plot its advancement in this situation it will look more like a step than a series of spikes.

Ramps The trehsold should be small enough to not create any false positive, patches that are traversable but were classified as not. So, we let the robot walk up hill on the $slope_rocks1$ map with a height scaling factor set to 5. We knew from empirical experiment that the robot is able to climp this steep ramp, the advancement is showed in figure 1.19. The mean ≈ 0.4cm over a $\Delta t = 2$, an impressive value considering the steepest of the surface. We can use this information combined with the previous experiment to choose a threshold that is beetween the upper bound of *bumps* and beetween the lower bound of *slope_rocks1*. This will ensure to minimize the false positive. A good value is $tr_{\Delta t=2s} = 20cm$.

1.5 Estimator

In this section we described the choices behind the evaluated network architecture.



(a) -1cm (b) -3cm (c) -3cm (d) -6cm (e) 00cm

(f) 01cm (g) 02cm (h) 03cm (i) 05cm (j) 08cm

(k) 11cm (l) 14cm (m) 17cm (n) 20cm (o) 23cm

(p) 26cm (q) 30cm (r) 33cm (s) 35cm (t) 38cm

(u) 40cm (v) 43cm (w) 45cm (x) 47cm (y) 49cm

(z) 51cm (aa) 53cm (ab) 54cm (ac) 56cm (ad) 57cm

(ae) 59cm (af) 60cm (ag) 62cm (ah) 63cm (ai) 65cm

(aj) 66cm (ak) 67cm (al) 69cm (am) 70cm (an) 73cm

Figure 1.16. Sample of extracted patches from the train set ordered by advancement. The first patches have mostly obstacle close to the robot's head, while the latter have smooter surfaces.

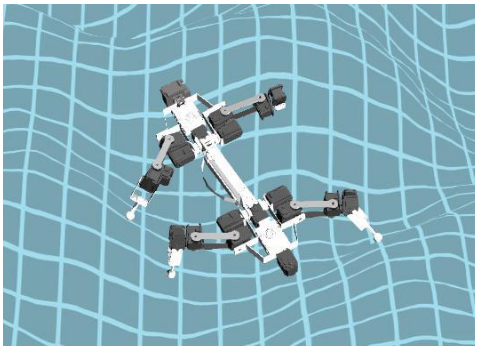


Figure 1.17. Krock tries to overcome an obstacle in the *bumps3* map.

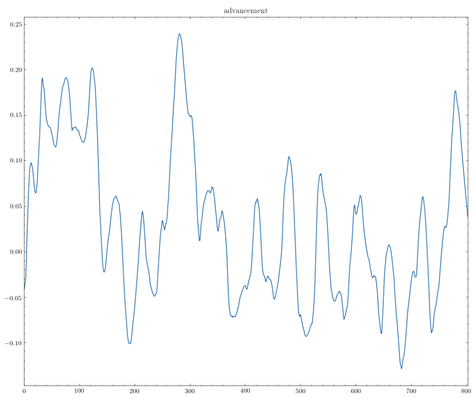


Figure 1.18. Advancement over time with $\Delta t = 2$ on *bumps3*.

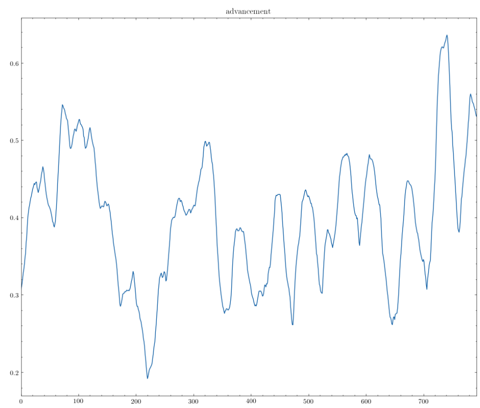


Figure 1.19. Advancement over time with $\Delta t = 2$s on *slope_rocks3*.

1.5.1 Vanilla Model

The original model proposed by Chavez-Garcia et all **?** is a CNN composed by a two 3×3 convolution layer with 5 filters; 2×2 Max-Pooling layer; 3×3 convolution layer with 5 filters; a fully connected layer with 128 outputs neurons and a fully connected layers with two neurons. Figure 1.20 visualizes the architecture.

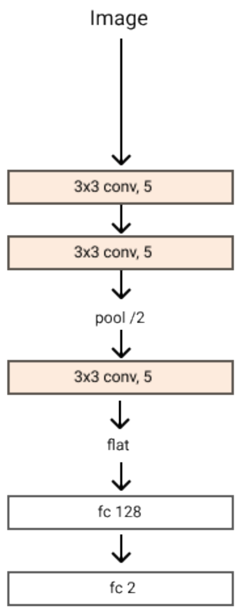


Figure 1.20. Vanilla model proposed by Chavez-Garcia et al. **?**. The rectangle represent the building block of each layer. Convolutiol layers are described by the kernel size, the number of filters and the stride.

1.5.2 ResNet

We adopt a Residual network, ResNet **?**, variant. Residual networks are deep convolutional networks consisting of many stacked R̈esidual Units ̈. Intuitively, the residual unit allows the input of a layer to contribute to the next layer's input by being added to the current layer's output. Due to possible different features dimension, the input must go through and identify map to make the addition possible. This allows a stronger gradient flows and mitigates the degradation problem. A R̈esidual Units ̈is composed by a two $3x3$ *Convolution*, *Batchnorm* **?** and a *Relu* blocks. Formally defined as:

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + h(\mathbf{x}) \tag{1.1}$$

Where, x and y are the input and output vector of the layers considered. The function $\mathcal{F}(\mathbf{x}, \{W_i\})$ is the residual mapping to be learn and h is the identity mapping. The next figure visualises the equation.

add resnet image or table

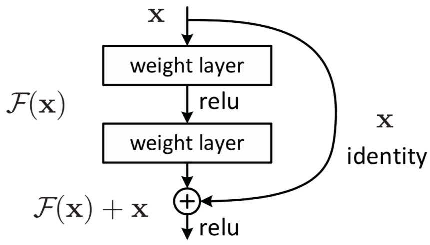


Figure 1.21. *Resnet* block **?**

When the input and output shapes mistmatch, the *identity map* is applyed to the input as a $3x3$ Convolution with a stride of 2 to mimic the polling operator. A single block is composed by a $3x3$ *Convolution*, *Batchnorm* and a *Relu* activation function.

1.5.3 Preactivation

Following the recent work of He et al. **?** we adopt *pre-activation* in each block.*Pre-activation* works by just reversing the order of the operations in a block.

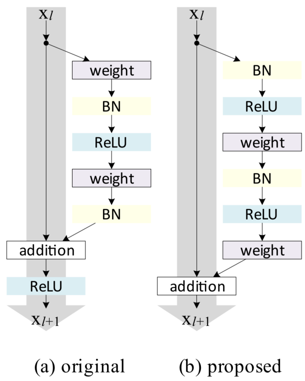


Figure 1.22. *Preactivation* **?**

1.5.4 Sqeeze and Excitation

Finally, we also used the *Squeeze and Excitation* (SE) module **?**. It is a form of attention that weights the channel of each convolutional operation by learnable scaling factors. Formally, for a given transformation, e.g. Convolution, defined as $\boldsymbol{F}_{tr} : \boldsymbol{X} \mapsto \boldsymbol{U}$, $\boldsymbol{X} \in mathbbR^{H' \times W' \times C'}$, $\boldsymbol{U} \in \mathbb{R}^{H \times W \times C}$, the SE module first squeeze the information by using average pooling, $\boldsymbol{F}_{sq}$, the it excitates them using learnable weights, $\boldsymbol{F}_{ex}$ and finally, adaptive recalibration is performed, $\boldsymbol{F}_{scale}$. The next figure visualises the SE module.

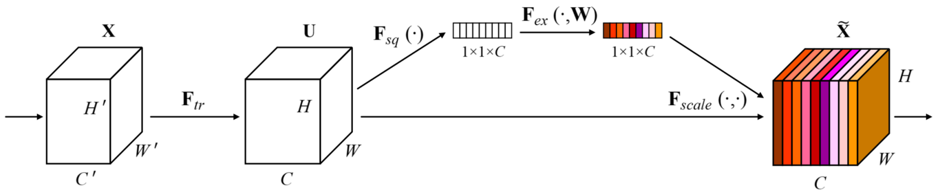


Figure 1.23. *Squeeze and Excitation* **?**

1.5.5 MicroResNet

Our network is composed by n ResNet blocks, a depth of d and a channel incrementing factor of 2. Since ResNet assumed an input size of 224×224 and perform an aggressive features extraction in the first layer, we called it *head*, as showed in we decided to adopt a less aggressive convolution. ref to Resnet Table We tested two kernel sized of 7×7 and 3×3 with stride of 2 and 1 respectively. Lastly, we used LeakyReLU **?** with a negative slope of 0.1 instead of ReLU to allow a better gradient flow during backpropagation. LeakyRelu is defined as follows

$$LeakyRelu(x) = \begin{cases} x & \text{if } x > 0 \\ 0.1x & \text{otherwise} \end{cases} \tag{1.2}$$

We called this model architecture *MicroResNet*. We evaluated $n = [1, 2], d = 3$ with and without squeeze and excitation and with the two differents *head*'s convolution. All the networks have a starting channel size of 16. Table **??** shows some of the architecture from top to bottom with, while figure 1.24 visualizes the final architecture we adopted the architecture with initial features size of 16 and stride of 2.

this table sucks

Our models have approximately 35 times less parameters than the smalles ResNet model, ResNet18, that has 11M parameters. To simplicity we will use the following notation to describe each architecture variant: `MicroResNet-3x3/7x7-/SE`.

ask omar help to add margin in the rows

add model picture

1.6 Normalization

Before feeding the data to the models, we need to make the patches height invariant to correctly normalize different patches taken from different maps with different height scaling factor. To do so, we subtract the height of the map corresponding *Krock*'s position from the patch to correctly center it. The following figure shows the normalization process on the patch with the square in the middle.

1.7 Data Augmentation

Data augmentation is used to change the input of a model in order to produce more training examples. Since our inputs are heightmaps we cannot utilize the classic image manipulations such as

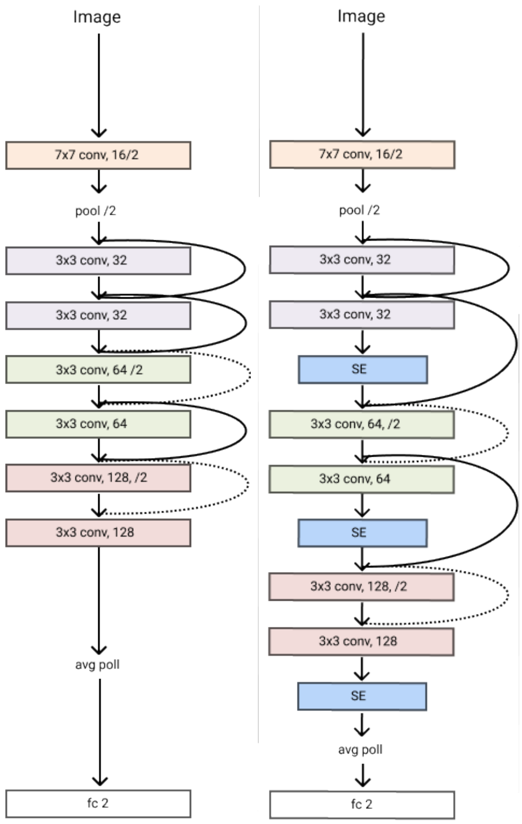
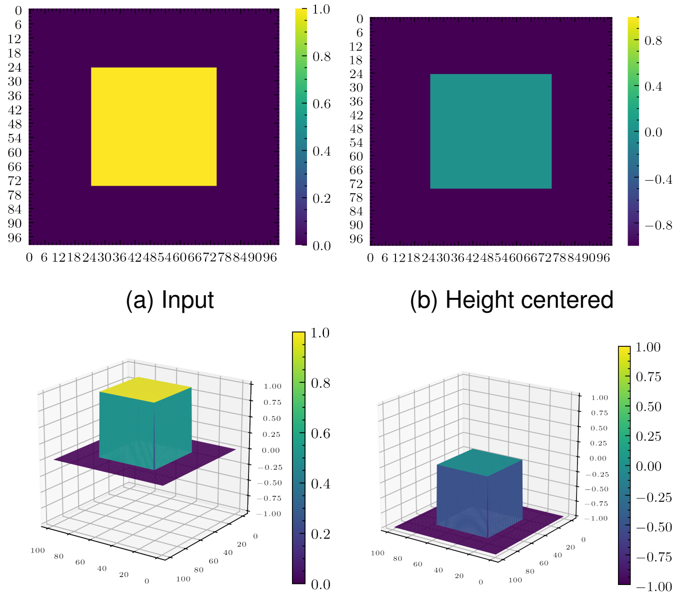


Figure 1.24. MicroResNet with initial features size of 16 and stride of 2 with and without the Squeeze and Excitation module. The rectangle represent the building block of each layer. Convolutiol layers are described by the kernel size, the number of filters and the stride. Lines and dashed lines between layers represent the residual operations and the shortcut respectively.

Input	$(1, 78, 78)$			
Layers	3×3, 16 stride 1		7×7 16 stride 2	
	$2 \times\ 2$ max-pool			
	$\begin{bmatrix} 3 \times 3, & 16 \\ 3 \times 3, & 32 \end{bmatrix}$ x 1			
	SE	-	SE	-
	$\begin{bmatrix} 3 \times 3, & 32 \\ 3 \times 3, & 64 \end{bmatrix}$ x 1			
	SE	-	SE	-
	$\begin{bmatrix} 3 \times 3, & 64 \\ 3 \times 3, & 128 \end{bmatrix}$ x 1			
	SE	-	SE	-
	average pool, 1-d fc, softmax			
Parameters	313,642	302,610	**314,282**	303,250
Size (MB)	5.93	5.71	**2.41**	2.32

Table 1.2. MicroResNet architecture. First layer is on the top. Some architecture's blocks are equal across models, this is shows by sharing columns in the table.

??



(a) Input (b) Height centered

(c) Input (d) Height centered

Figure 1.25. Normalization process. Each patch is normalized by subtracting the height value corresponding to the robot position to center its height.

shifts, flips, and zooms. Imagine that we have a patch with a wall in front of it, if we random rotate the image the wall may go in a position where the wall is not facing the robot anymore, making the image now traversable with a wrong target. We decided to apply dropout, coarse dropout, and random simplex noise since they are traversability invariant. To illustrate those techniques we are going to use the same square patch showed before 1.25.

1.7.1 Dropout

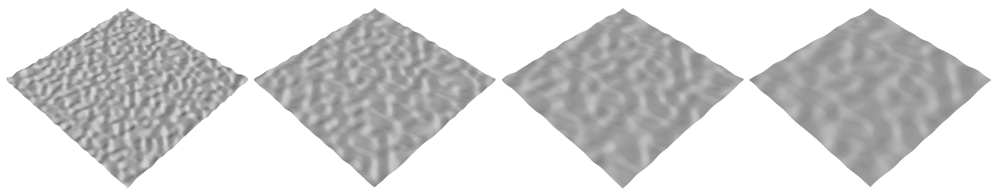
Dropout is a technique to randomly set some pixels to zero, in our case we flat some random pixel in the patch.

1.7.2 Coarse Dropout

Similar to dropout, it sets to zero random regions of pixels with defined boundaries.

1.7.3 Simplex Noise

Simplex Noise is a form of Perlin noise that is mostly used in ground generation. Our idea is to add some noise to make the network generalize better since lots of training maps have only obstacles in flat ground. Since it is computationally expensive, we randomly fist apply the noise to five hundred images with only zeros. Then, we randomly scaled them and add to the input image.

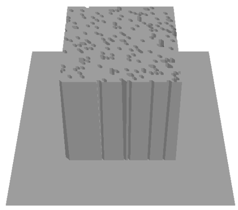


(a) Features size = 10 (b) Features size = 20 (c) Features size = 30 (d) Features size = 40

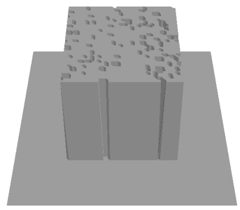
Figure 1.26. Simplex noise on flat ground. The feature size corespond to the amount of noise we introduce in the surface. A lower value produces noisy grounds, while a bigger one smoother terrains.

Figure **??** shows the tree data augmentation techniques used applied the input image. To ensure we do create untraversable patches from traversable patch we limited the coarse dropout region to only few centiments and we apply a smoother simplex noise on traversable patches. In detail,

un all the traning epochs, we augmented 80% of the input images with dropout and coarse dropout. Dropout has a probability between 0.05 and 0.1 and coarse dropout has a probability of 0.02 and 0.1 with a size of the lower resolution image from which to sample the dropout between 0.6 and 0.8. Simplex noise was applied on the 70% of the training data samples with a feature size between 1 and 50 with a random scaling factor between $15-25$ and $5-15$ from traversable and not traversable patches respectively.

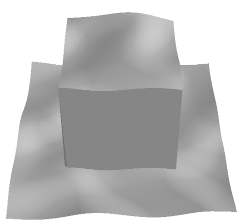


(a) Dropout

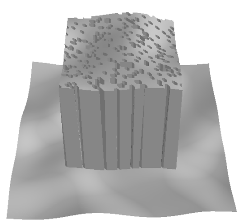


(b) Coarse Dropout

f



(c) Simplex Noise



(d) Final result

Figure 1.27. Data augmentation applied on a patch. First we randomly set to flat some small regions of the ground. Then, we slighty mutate the surface using simplex noise.

1.8 Tools

We quickly list the most important tools and libraries adopted in this project:

- ROS Melodic
- Numpy
- Matplotlib
- Pandas
- OpenCV
- PyTorch
- FastAI
- imgaug
- mayavi

The framework was entirely developed on Ubuntu 18.10 with Python 3.6.

1.8.1 ROS Melodic

The Robot Operating System (ROS) **?** is a flexible framework for writing robot software. It is *de facto* the industry and research standard framework for robotics due to its simple yet effective interface that facilitates the task of creating a robust and complex robot behavior regardless of the platforms. ROS works by establishing a peer-to-peer connection where each *node* is to communicate between the others by exposing sockets endpoints, called *topics*, to stream data or send *messages*.

Each *node* can subscribe to a *topic* to receive or publish new messages. In our case, *Krock* exposes different topics on which we can subscribe in order to get real-time information about the state of the robot. Unfortunately, ROS does not natively support Python3, so we had to compile it by hand. Because it was a difficult and time-consuming operation, we decided to share the ready-to-go binaries as a docker image.

1.8.2 Numpy

Numpy is a fundamental package for any scientific use. It allows to express efficiently any matrix operation using its broadcasting functions. Numpy is used across the whole pipeline to manipulate matrices.

1.8.3 Matplotlib

Almost all the plots in this report were created by Matplotlib, is a Python 2D plotting library. It provides a similar functional interface to MATLAB and a deep ability to customize every region of the figure. All It is worth citing *seaborn* a data visualization library that we inglobate in our work-flow to create the heatmaps. It is based on Matplotlib and it provides an high-level interface.

1.8.4 Pandas

To process the data from the simulations we rely on Pandas, a Python library providing fast, flexible, and expressive data structures in a tabular form. Pandas is well suited for many different kinds of data such as handle tabular data with heterogeneously-typed columns, similar to SQL table or Excel spreadsheet, time series and matrices. We take advantages of the relationa data structure to perform custom manipulation on the rows by removing the outliears and computing the advancement.

Generally, pandas does not scale well and it is mostly used to handle small dataset while relegating b̈ig dataẗo other frameworks such as Spark or Hadoop. We used Pandas to store the results from the simulator and inside a Thread Queue to parse each *.csv* file efficiently.

1.8.5 OpenCV

Open Source Computer Vision Library, OpenCV, is an open source computer vision library with a rich collection of highly optimized algorithms. It includes classic and state-of-the-art computer vision and machine learning methods applied in a wide array of tasks, such as object detection and face recognition. We adopt this library to handle image data, mostly to pre and post-process the heightmaps and the patches.

1.8.6 PyTorch

PyTorch is a Python open source deep learning framework. It allows Tensor computation (like NumPy) with strong GPU acceleration and Deep neural networks built on a tape-based auto grad system. Due to its Python-first philosophy, it is easy to use, expressive and predictable it is widely used amoung researches and enthusiast. Moreover, its main advantages over other mainstream frameworks such as TensorFlow **?** are a cleaner API structure, better debugging, code shareability and an enormous number of high-quality third-party packages.

1.8.7 FastAI

FastAI is library based on PyTorch that simplifies fast and accurate neural nets training using modern best practices. It provides a high-level API to train, evaluate and test deep learning models on any type of dataset. We used it to train, test, and evaluate our models.

1.8.8 imgaug

Image augmentation (imgaug) is a python library to perform image augmenting operations on images. It provides a variety of methodologies, such as affine transformations, perspective transformations, contrast changes and Gaussian noise, to build sophisticated pipelines. It supports images, heatmaps, segmentation maps, masks, key points/landmarks, bounding boxes, polygons, and line strings. We used it to augment the heightmap, details are in section 1.7

1.8.9 Mayavi

Mayavi is a scientific data visualization and plotting in python library. We adopt it to rendered in 3D all the surfaces used in our framework.