
# Extended Reality Lab for Mars Experiments: Mars Xlab

## Executive summary

**Early technology development**

*Open Space Innovation Platform (OSIP) campaign,*
*"New ideas to make XR a reality",*

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### Activity summary:

Mars Xlab aimed to develop an innovative virtual lab for Mars experiments, where AI methods were used to improve orbital imagery resolution, as well to obtain terrain features based on local images from rovers. Two different methods were used to recreate the virtual environment. The first one was dedicated to process low resolution images from orbital information and the use of AI to increase the resolution of these images. The second approach was related to the 3D recreation of high-resolution rocks based on a two stages approach, in which AI was used to detect rocks on rover local images to later recreate them in 3D.

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# EXTENDED REALITY LAB FOR MARS EXPERIMENTS (MARS XLAB)

**Executive Summary Report**

## 1. INTRODUCTION

Virtual reality environments have been widely used to train astronauts [1] and demonstrate robotic technologies [2] in different scenarios on Space. These scenarios have been commonly created in a similar fashion to the real one. One of the most recent examples is the scenario provided in the NASA MarsXR 2 Challenge [1], which is used to create extravehicular activity research for the surface of Mars. However, most of them are synthetically generated and do not take into consideration real data. Lately, visual data collected in space missions is helping to better understand remote planets. This information is supporting the recreation of Mars environments through 3D visualization tools. An example of these tools is the geographic information system (GIS) generated by the Freie Universität Berlin [3]. This tool recreates 3D views from different areas of Mars, including the Jezero Crater[2]. In the case of rover navigation, the use of virtual environments allows to extensively test the Guidance, Navigation and Control (GNC) architecture without requiring a real rover and scenario. However, the use of synthetic scenarios reduces the usefulness of the simulation environment, since the tests are not as representative as they could. For this reason, the use of virtual reality that includes real 3D visualization of the surface of remote planets, based on visual data collected, arises as a very interesting method to test planetary exploration robots on the same scenario in which the system will later operate. These photorealistic virtual environments provide different advantages to simulate rover navigation: they allow to test the rover locomotion subsystem on very realistic surfaces to estimate their later performance; and perception and localisation algorithms can be implemented, emulating visual information and feeding it to the navigation methods. This is, conclusively, the maximum exploitation of the software and hardware in the loop concepts.

The main objective of this activity was to design and develop an innovative virtual lab for Mars experiments, where AI methods are used to improve orbital imagery resolution, as well to obtain terrain features based on local images from rovers. Two different methods were used to recreate the virtual environment. The first one was dedicated to process low resolution images from orbital information. The main contribution in this sense was the use of AI to increase the resolution of these images. The generated textures were integrated along with Digital Terrain Maps (DTM) to recreate the surface in 3D. The second approach was related to the 3D recreation of high resolution rocks. Rocks were recreated based on a two stages approach, in which AI was used to detect rocks on rover local images to later recreate them in 3D using GAN Neural Networks. Finally, high-resolution textures were obtained from available sources on Internet, placing them on the virtual scenario depending on the NOAH-H deep-learning based terrain classification system [4], first obtaining the segmentation of a partial area of Mars and, second, including the corresponding high resolution textures.

## 2. SUPER-RESOLUTION FOR ORBITAL IMAGERY

To create ultra-realistic virtual scenarios of the Martian surface, it is necessary to use high-resolution images of the terrain. The maximum available resolution from Martian orbital images is $0.25m/pixel$ for grayscale HiRiSE images, and $12.5\ m/pixel$ for true color High-Resolution Stereo Camera (HRSC) images. Although $0.25m/pixel$ is considered high resolution, it is not enough for soil textures according to the size of a Martian rover (in the order of a few meters). As a result, to provide highly-detailed soils within the virtual environment, a Super-resolution component has been developed. This component aims to process low-resolution Martian orbital imagery to increase their resolution.

[1] $https://bit.ly/MarsXR_XOSS$

[2] https://maps.planet.fu-berlin.de/jezero/#vr

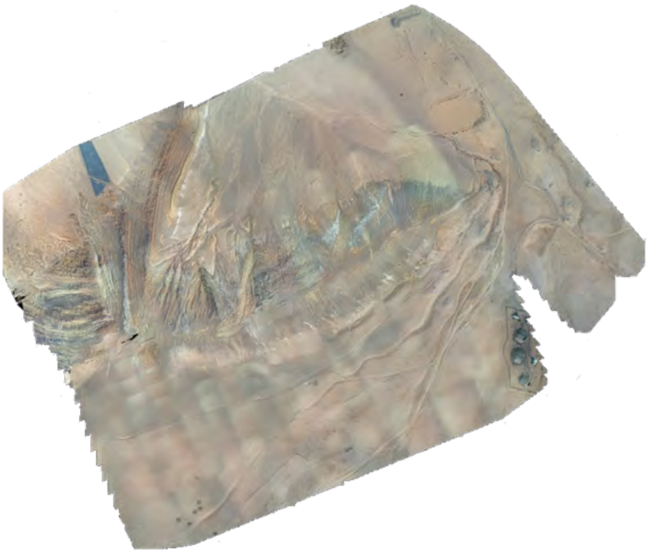


Figure 1: Orthomosaic of La Caldera del Cuchillo, Lanzarote, Canary Islands, Spain. It was obtained by aerial surveying of the area.

For this purpose, the Super-Resolution Generative Adversarial Network (SRGAN) method [5] has been selected. Summarizing, SRGAN is a feed-forward convolutional neural network. At its core, there are B residual blocks followed by two convolutional layers with small 3x3 kernels and 64 feature maps, and several batch-normalization layers with parametric ReLU activators are located at the end of the network. Once an image comes out of the residual blocks, a x4 resolution image is obtained thanks to the combination of two sub-pixel convolution layers. For training, SRGAN converts the input high-resolution images into low-resolution ones by applying a Gaussian filter followed by a down-sample operation. Then, the network is trained to obtain the original super-resolution images using their low-resolution equivalent.

Regarding the training dataset for SRGAN, it should contain high-resolution images with similar features as the images whose resolution is to be increased later. Therefore, during this work a dataset was obtained from an Earth Mars-like scenario at La Caldera del Cuchillo[3], in Lanzarote, Canary Islands, Spain. Using a drone, an extensive number of images of the landscape were obtained. Later, the orthonormal images were post-processed using Pix4d[4] to generate an aerial orthomosaic of the area of interest, which is shown in Figure 1. This orthomosaic was divided into smaller high-resolution images to generate the final aerial orthonormal dataset used for training the Super-resolution network. Remark that, in addition to the aerial images, the drone was flown at low altitude (1.5-2 $m$) to get images from a rover navigation camera point of view. Those images were used for the terrain features detection and modeling, as explained later.

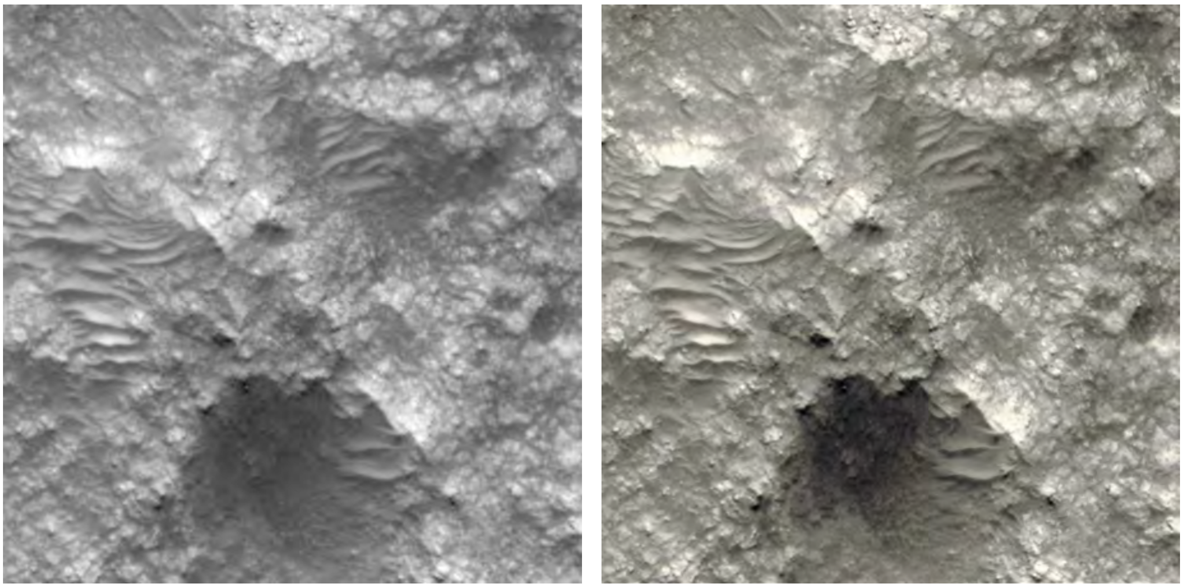
After training SRGAN with the dataset from Lanzarote, the Super-resolution component was able to increase the resolution Martian HiRiSE images with an 4x factor approximately. An example is shown in Figure 2, where Figure 2a shows the original grayscale image from HiRiSE, with a resolution of $0.25\ m/pixel$, and 2b shows the image obtained after applying Super-resolution. The result is a high-resolution image of approximately $0.06\ m/pixel$, in which, as can be observed, the level of detail is significantly increased.

## 3. TERRAIN FEATURES DETECTION AND 3D MODELLING

General features of a landscape such as the presence of sandy or rocky terrains need to be identified to create a realistic virtual scenario. We used the "Novelty or Anomaly Hunter - HiRISE" NOAH-H [6] to obtain the segmentation masks of Mars areas of interest. Additionally, 3D models of relevant features such as rocks are necessary to create a realistic virtual scenario. A two-stage approach is adopted to fulfill this task. The first stage is devoted to the automatic identification and extraction of 3D features from singles images taken by rovers in real conditions. The second task is dedicated to create 3D models using the previously identified features.

For the terrain features identification stage, Yolov5 neural network was integrated. Yolov5 [7] is based on YOLO (You Only Look Once) architecture, a single-shot image detector which is trained using features of the whole image instead of

[3] https://www.google.es/maps/@29.0885978,-13.6491243,939m/data=!3m1!1e3
[4] https://www.pix4d.com/



(a) (b)

Figure 2: Obtained high-resolution image (b) after applying Super-resolution to a low-resolution orbital grayscale HiRiSE image of the Martian surface (a). The resolution was increased from $0.25\ m/pixel$ to approximately $0.06\ m/pixel$.

dividing the image in feature regions. This characteristic allows for fast inference times. For the 3D model reconstruction stage, Unicorn GAN (Generative Adversarial Network) [8] was implemented. Unicorn uses monocular images to reconstruct objects in 3D. Given an input image, the network predicts four parameters, which are used to generate the output 3D model: shape, texture, pose and background. Starting from a 3D prototype figure such as a sphere, Unicorn performs modifications to the model until it reaches a similar monocular image to the one provided from different perspectives. Furthermore, the neural network generates a texture with the main features of the images used for the training.

Both Yolov5 and Unicorn GAN were trained using on-site images extracted from Lanzarote and Mars Yard datasets [9]. The trained Yolov5 network was later used to identify features on images taken by Perseverance rover Navcam on Mars (see Fig. 3). The detected monocular features were introduced as input into Unicorn GAN to produce the 3D models (an example is depicted in Fig. 4) which were incorporated into the virtual scenario.

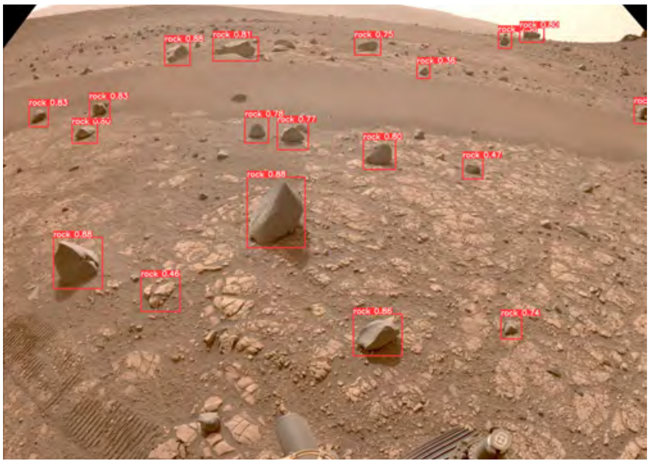


Figure 3: Identified features using the trained Yolov5 neural network on Perseverance rover Navcam on Mars.

Figure 4: On the left, identified rock with Yolov5 from Perseverance rover Navcam. On the middle and right images, reconstructed 3D model from two points of views using Unicorn GAN.

Figure 5: ExoTeR rover in the virtual environment.

## 4. IMMERSIVE VIRTUAL SCENARIO

The immersive scenario was developed using Unreal Engine 5, a photorealistic videogame engine. Moreover, it includes a physics engine, which together with its realism, makes it a useful tool for the simulation of autonomous algorithms in rovers. Thus, a model of ExoMars Testing Rover (ExoTeR) [10], a scaled-down model of the ExoMars Rover, was also developed (see Fig. 5).

The main landscape was created with height information obtained from HiRISE images, which have a resolution of $1m/pixel$. The textures were replicated using the terrain segmentation provided by NOAH-H. Nonetheless, HiRISE images do not provide true color information, thus HiRISE images were colorized using the HRSC images as a reference by applying the colorization methods proposed in [11].

## 5. CONCLUSIONS

This paper proposed the use of real datasets to recreate an inmersive virtual environment from Mars. This approach required to solve different challenges related to the low quality of the information and lack of details. To solve the first issue, we proposed the use of super-resolution techniques, which were able to increase the resolution of orbital imagery up to x4. However, we realized that even increasing the resolution, it would not be enough to recreate a virtual environment that would support testing novel navigation methods for rovers. Therefore, we decided to include a new very high resolution layer with similar textures to the obtained terrain segmentation from NOAH-H. Furthermore, we needed to include rocks in the most realistic manner. For this purpose, we obtained real images from the Perseverance rover, and recreated them in 3D using SRGAN based methods. As results, we were able to recreate more than two hundred different rocks that were placed on the virtual environment. Finally, we integrated the ExoTeR rover testbed, to demonstrate we can simulate the rover motion on the realistic virtual environment. Testing novel perception and localization methods, and their corresponding perfomance analysis is something proposed as future work.

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