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Department of Earth Science and Engineering
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Independent Research Project
Final Report

Developing a semi-automated tool to simulate Lava Flows in Magellan SAR imagery on Venus

by

Iona Chadda

Email: iona.chadda23@imperial.ac.uk

GitHub username: edsml-iyc23

Repository: ese-msc-2023/irp-iyc23 (github.com)

Supervisors:

Gerard Gallardo i Peres

Dr. Philippa Mason

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Abstract

This report investigates the possibility of generating synthetic lava flows on radar images, from the Magellan mission data set.

The characteristics of Venusian lava flows are investigated, with the aim of reproducing similar synthetic lava flows on preexisting radar images.

Machine learning techniques such as training a GAN model on real lava flow images, were used to generate imitations of the lava flow textures seen in radar images.

Existing research has examined the use of remote sensing to monitor lava flows on earth as well as generating synthetic satellite images using machine learning techniques. However there is limited research accomplishing these tasks solely using single band radar satellite images, thus making the current project a unique area of study.

The outcome of this project is the development of a tool that can automatically create a lava flow for a given location on a radar image.

Introduction

Literary Review

Research into lava flows with radar imagery offers numerous applications. For earth observation, it can be used for lava flow monitoring and prediction which can help assess the risk associated with volcanic hazards. Radar imagery can also be applied to the discovery of lava flows on Venus. SAR data is very important in this context as, unlike earth observation, SAR is the only type of remote sensing that can detect anything on the planet's surface due to the thick atmosphere that block most other waves of the electromagnetic frequency (Campbell and Hensley, 2024).

There has been substantial volcanism in Venus's history resulting in over 80% of the surface being covered in volcanic deposits, with lava flows on the scale of the largest eruptions on Earth (Roth and Wall, 1995). The Magellan mission provides the highest quality of observation so far, leading to the volcanic plains being detected (Roth and Wall, 1995). The different geologies and surface formations are observed as variation in the backscattering and new surfaces will show different scattering properties to old in the SAR Magellan images (Sulcanese et.al. 2024). Synthetic aperture radar (SAR) is a high-resolution ground observation radar with high-penetrating capability. It utilizes the pulse compression and the movement of the radar platform to generate 2-D images (Gao et.al. 2023). There has been significant research using SAR backscatter to observe volcanic eruptions, including mapping fresh lava flows (Dualeh, 2021). However in recent years there has been an increase in research using differential Interferometric Synthetic Aperture Radar (InSAR) for volcano monitoring (e.g., Ebmeier et al., 2018; Fournier et al., 2010; Pritchard et al., 2018), whereas using radar backscatter from individual SAR images is still under-exploited (Dualeh, 2021). Which, in the context of the Venus volcanic research, is a large research gap as single backscatter SAR images is the only data available to observe the surface of Venus.

Research Aim

Overall, advancing the area of SAR remote sensing on Venus will ultimately assist in the expansion on research on Venus' surface. This project aims to develop this area by creating a tool that can replicate the way that lava flows are represented in Magellan's radar images.

Research Background

To achieve this, there is a required understanding of the backscatter coefficient and overall texture associated with lava flows as they are the elements that need to be imitated to create a realistic-looking synthetic lava flow in a radar image.

In the SAR images, bright areas represent regions of higher radar backscatter, whereas dark areas indicate lower radar backscatter (Sulcanese et.al. 2024). The variations in the surface roughness affect the relative brightness of flows in the Magellan radar images, which can suggest differences in the age of state of preservation of separate flows (Sulcanese et.al. 2024). This is why the backscatter coefficient is an important variable to consider.

The backscatter is specifically the proportion of the transmitted electromagnetic pulse that the ground directs back toward the satellite and is described as the Radar Cross Section (RCS) or σ (Dualeh, 2021). After the backscatter is detected there is some post-processing done to calculate the backscatter coefficient as the RCS has to be calibrated and normalised to be the backscatter coefficient σ° (Dualeh, 2021). Conventionally, due to its high dynamic range, the radar backscatter is expressed in decibels $\sigma^\circ_{dB} = 10\log_{10}\sigma^\circ$ (Dualeh, 2021). The data will be presented in this form for this project.

The underlying variation is (RCS) backscatter coefficient is not the only source of information within a SAR image as the texture of an object is an important characteristic and can play a crucial part in identify different surface types. In the scope of this project lava flows will carry a unique texture that will help distinguish them from the rest of the radar image. Texture is expressed as the presence of certain shapes and patterns in the RCS (Oliver and Quegan, 2004).

An import characteristic of radar images that needs to be considered is image noise. Radar images innately have speckle noise which is the constructive and destructive interference from individual scatterers within a pixel, causing backscatter to change even in pixels that would otherwise remain stable between acquisitions (Dualeh, 2021). Speckle in SAR images can obscure signals in backscatter and complicate the data interpretation (Dualeh, 2021). Speckle influences our ability to estimate image properties therefore, it is central to information retrieval from individual SAR images (Oliver and Quegan, 2004). Thus it is important to denoise images before trying to identify features, but more importantly for this project it has to be replicated as creating a synthetic feature in a radar image it must also have speckle just as it has in a radar image.

The data that this project will be based on is the Magellan SAR experiment data, specifically the F-BIDR data, which is a mosaic construction of the BIDR data set which are long swaths of 300 pixels east west and 200,000 pixels north-south (Wall .et.al. 1995). BIDR pixels are the measure of the reflectance of the represented surface element, of diameter 75m, expressed in decibels, relative to a model of the average Venusian reflectance (Wall .et.al. 1995).

This project will require achieving the following objectives:

Objective 1: Explore the backscatter coefficient, and work out a way to segment the lava flows and calculate the mean backscatter coefficient of different flows.

Objective 2: Replicate the texture of the radar image using a Generative Adversarial Network. This will be trained on images of the dB backscatter values of real lava flows so that it can then generate realistic lava texture depicted on radar backscatter images.

Objective 3: Create a semi-automatic tool that can implement and post-process the generated texture with a given mean backscatter value into a shape that could be a lava flow.

Methodology

The tool should be able to produce lava flows that has a mean backscatter coefficient equal to other identified lava flows, as it will allow the extension of real lava flows in the radar images. To be able to achieve this it is important to have a function that can identify the lava flows in the image. Furthermore, automatically identifying the lava flows is key in obtaining the training data set for the model that will used to generate the lava texture.

There were six images obtained the Magellan Database, each displayed as the backscatter coefficient from the SAR dataset.

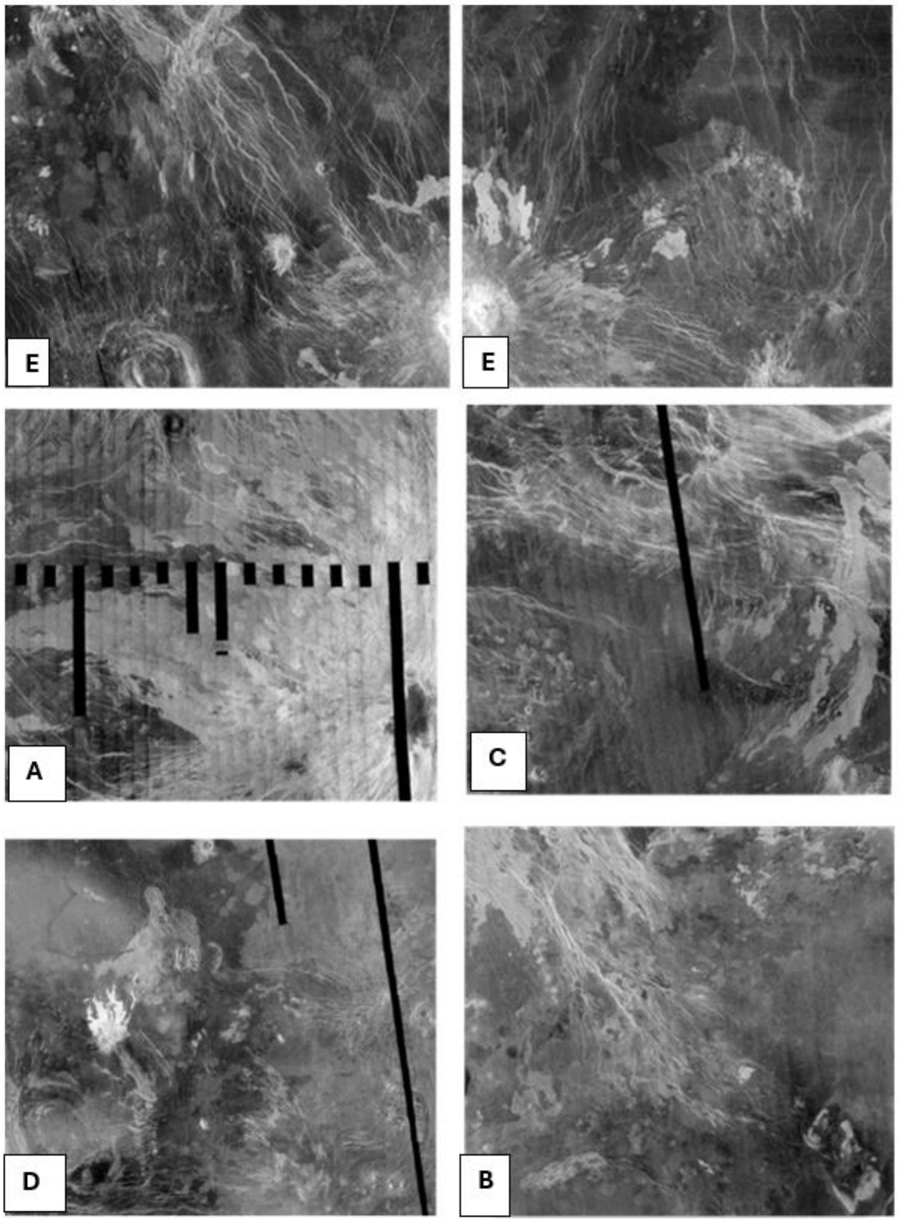

Figure 1 A depiction of the 6 Radar images used to train the lava generation tool.

These radar images were selected for building the generating lava flow tool as there were distinct lava flows in each of them which could then be used as a template for what lava flows should look like. The locations of these radar images are depicted in figure 2.

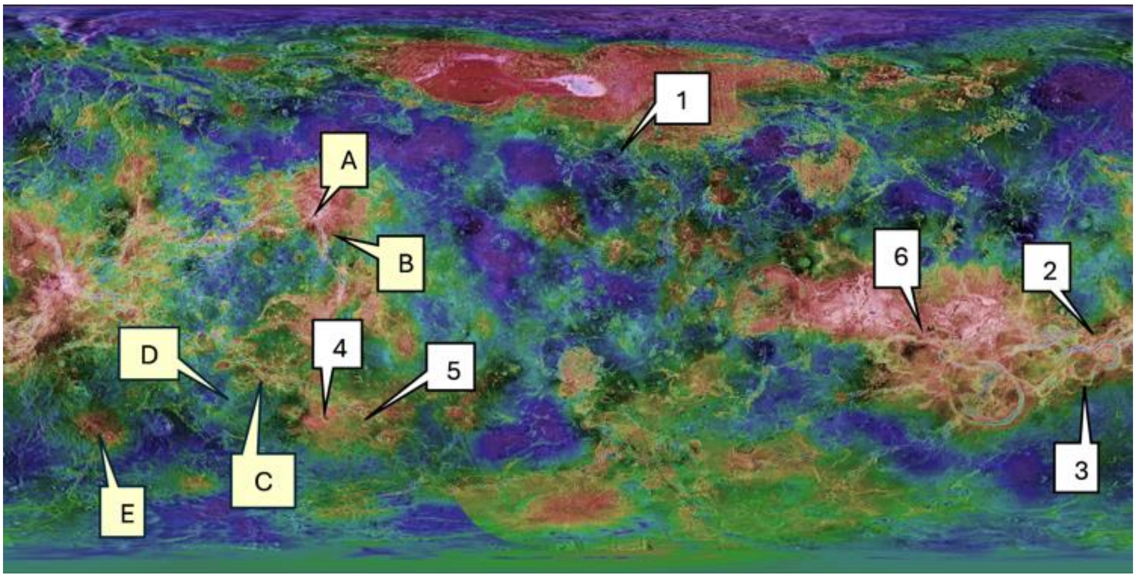

Figure 2 The background image is Venus Magellan Global C3-MDIR Colorized Topographic Mosaic 6600m (USGS, 2024). Locations A,B,C,D and E show the locations of the Radar images that were used as a bases for creating the lava creation tool. Locations 1,2,3,4,5 and 6 are the locations in which radar images were taken to test the tool out on.

Objective 1: Image Segmentation

The images are denoised to make the segmentation easier. Two means of denoising are used, the lee filter and a gaussian blur filter. Both filters work effectively but the tool is designed so the user can input a choice of denoising filter as the lee filter preserves the edges better, but the gaussian removes a larger amount of the noise.

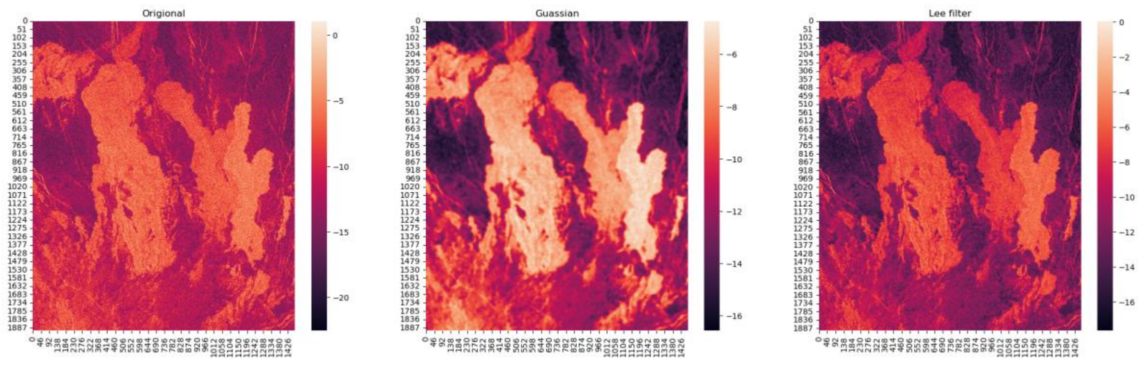

Figure 3 An example of how the Lee filter and Gaussian blur filter effects the radar image.

The separation of the lava flows is done using unsupervised, non-parametric machine learning techniques such as k-means clustering and Gaussian Mixture model. To accommodate for the users' own preference the function implements both a Gaussian Mixture model and a k-means clustering algorithm, then the two segmentations are applied and visualised, allowing the user to decide which method is more appropriate for their use. The segmentation is visualised as the classified image and then as the histogram pixel values plots, it allows the user to visually decide which classification method works best in their specific case.

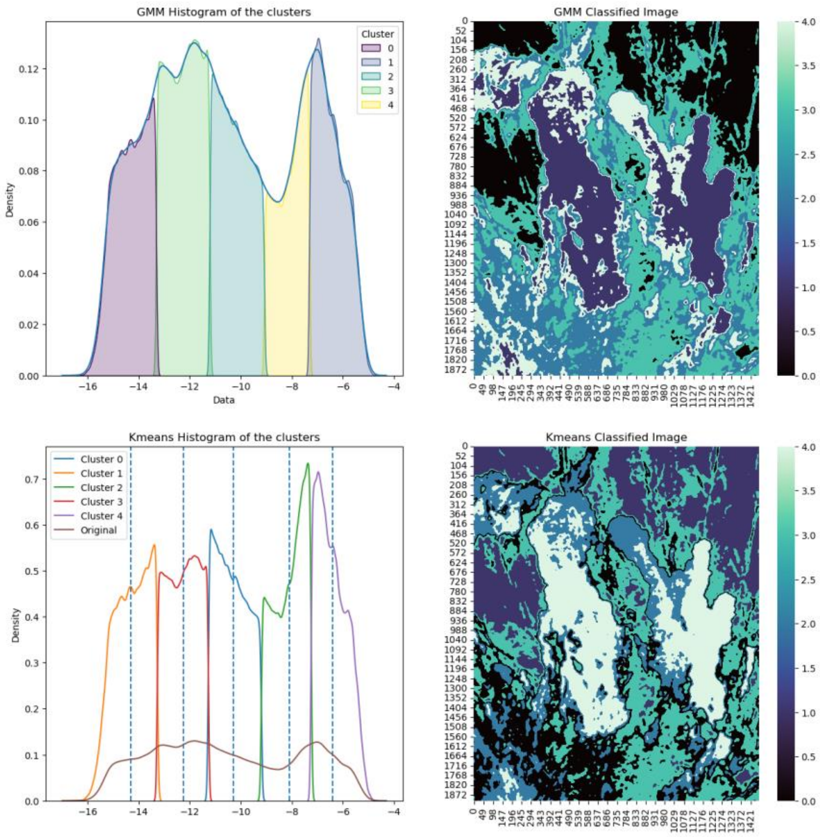

Figure 4 Example of the lava flow segmentation

In extracting areas of lava flows to use the texture to train the neural network, the images are segmented into five clusters, the cluster that had the most values between -9 and -12 being used, as in the images selected to abstract the lava texture, the mean backscatter coefficient was most commonly between these two values.

However it is noted that these are unique for the radar images chosen as the mean backscatter coefficient is dependent on many variables, such as angle between the satellite and surface being measured, meaning the mean backscatter will vary with latitude, in addition to the factors such as slope angle. Furthermore it is important to note that the method used to detect and extract the lava flows is not foolproof as it is solely determining the areas in which there are lava flows on the average back scatter coefficient. Though this is not a highly accurate or exhaustive method however, it is successful at carrying out this task and as it is an intermediate step any errors generated will not affect the final outcome. The lava flows are identified and then a mask is created to extract those areas. The image is split into tiles and the tiles that are within the mask are stored as the training data for the texture generation model.

Objective 2: Texture Generation

To be able to replicate the texture shown in lava flows in radar images, a deep neural network model is used to generate synthetic images that are similar to the training data of the model. Originally this was going to be done with a diffusion model, which would learn how to de-noise images through a set of iterations. This model type is based on the premise of the Markov chain. The training data used are 28x28 pixel samples that are obtained by splitting up a large lava flow image into 28x28 pixel squares. However this diffusion model is discarded as producing a large number of these samples takes too long as the images are generated by inputting noise and then iterating over the noise until an image similar to the training data is produced.

In addition to this problem, this image produced does not reflect the lava texture effectively on a larger scale. So instead the model will be trained on data using larger texture samples that better captures the overall texture of the lava.

The model used is a GAN model, specifically a deep convolutional GAN, the model's architecture was based off of (Radford et.al. 2015) as GAN models can producing images quickly and the deep convolutional layers are useful in detecting visual patterns in the image.

GAN Model Overview

The GAN model is made up of two neural networks, a generator and a discriminator, where the generator learns how to create images like the training data and the discriminator learns how to discriminate between the real images and the fake ones produced by the generator, thus they train in an adversarial manner (Abady et.al. 2022).

The model is trained on 128x128 sized samples of lava flows which is the same as the model's output, as a 'high-resolution synthetic image can only be obtained by stitching together multiple smaller patches' (Abady et.al. 2022). The model uses a batch norm for the generator and the discriminator and all the layers in the model convolutional layers instead of pooling layers. The activations used are ReLU for the generator (apart from the output layer which as Tanh), and for the discriminator it is LeakyReLU for all the layers apart from the last, which is a sigmoid (Radford et.al. 2015). In addition, the generator has no fully connected hidden layers, as based on the architecture displayed in Radford et.al. 2015. A gradient penalty is included during training to help improve the results, and Adam is used as an optimizer.

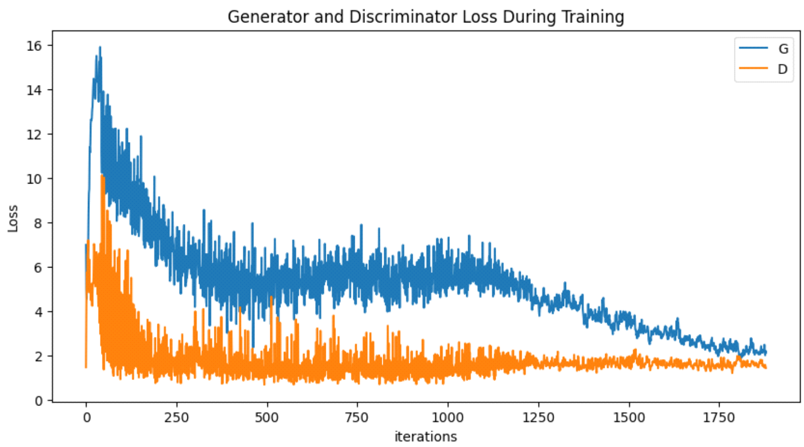

Figure 5 The loss plot from training the GAN model. This was run on a GPU

The loss from the training is acceptable for the GAN model as the discriminators' loss stabilises over time whilst the generator's loss decreases over the iterations.

The trained model produces 128x128 tiles of normalised lava texture, without a significant amount of noise, which leads the tiles to look artificial and structured. This means that the postprocess is important for adding a level of random noise to make the images look more natural.

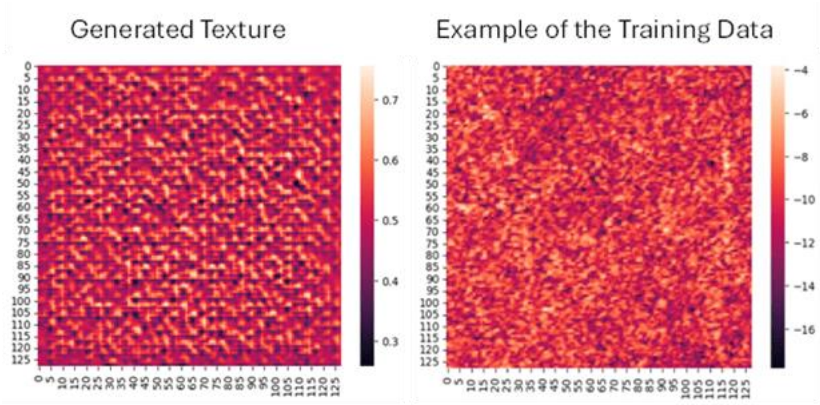

Figure 6 Example of the training data and the output of the DCGAN model

Objective 3: Creating the Lava Flow Shape

The aim is to produce a shape that is randomly generated whilst having a natural looking lava flow shape. The issue with completely randomly producing a polygon is that the edges look sharp and unnatural. To fix this issue, a Bezier curve is added between the randomly generated points, thus smoothing out the sharp edges of the polygon. In addition, noise is added to the polygon shape in the form of Perlin noise so that the boundary of the shape naturally fluctuates. The location of the polygon on the raster image is chosen randomly, or it can be located at a set of coordinates given by the user.

The polygon coordinates is converted into a pixelated image with the goal being to create a mask of the generated lava flow shape. To do this the vertices are joined by using the Bernstein line algorithm. This is mainly effective however it struggles to join up all the points which is because the algorithm is not very effective on shallow negative slops that would be needed to join up certain points. To fix this problem, the values of the pixels that are part of the polygon are increased to a high value and put a gaussian blur filter over the shape with a high sigma value, which meant that all the pixels near the polygon were given a value greater than zero. Flood fill function is used to fill the polygon with a pixel value.

With the filled polygon shape projected back onto the original radar image, the maximum number of size 128x128 pixels tiles to fill the shape is calculated. The trained model is used to generate that number of tiles to place onto the radar image, and the lava shape mask is also used on the lava image to create the right shape.

Post-Processing the synthetic Lava Flow

To make the image look realistic, a level of noise is added to the samples. There are two types of noise added to the images, speckle and gaussian noise. Gaussian noise is added to each of the 128x128 pixel tiles. The speckle is added to the lava flow after the tiles have been stitched together. This helps remove the gridded look, from having constructed the flow from tiles.

An important step is to change the mean backscatter coefficient of the generated lava flow, so that it can be made as an extension of a real lava flow, thus having the same mean backscatter value. Firstly, the code is designed so that the user can input a coordinate that would be used to identify a lava flow that wants to be extended. The image is segmented using the same method in which the lava flows were extracted from images used for the training data, however only the one lava flow that is located on the given coordinate is extracted. From this the mean and standard deviation of the lava flow is calculated. The generated lava flow is then modified to have the same mean and standard deviation. After this is done the speckle is added to the lava flow which allows the synthetic lava flow to blend into the rest of the radar image.

Results

This section will look at how successful the tool is at creating lava flows from scratch as well as extending a real lava flow already in the image. This investigation will be done by testing the code on multiple of radar images at different altitudes and latitudes as a way of seeing how sustained the results are at reproducing artificial lava flows that cannot be distinguished from actual flows.

Each of the radar images have been taken from regions of different characteristics and locations, these regions are depicted in figure 2. The testing radar images are from different areas, compared to the images that the tool was based on, to see if the tool is generally applicable to any location on Venus.

Radar images 2, 3 and 6 are located on Aphrodite Terra, in which there is a high variation in the elevation, as it is a fracture terrain zone with a lot of tessera terrain and with many deep chasmata and coronae. This variety in the landscape differs to the predominant landscape type of Venus.

Radar image 1 is located just south of Ishtar Terra, which is an area that has a lot of volcanism, some even active, with areas of deformation and numerous volcanoes with the diameter >5km (Ogliore, 2023). This is also an area at a lower elevation than the other areas, furthermore it is located in the northern hemisphere, unlike the other locations.

Radar images 4 and 5 are located at Themis Regio, an area that has been interpreted as a hot spot (Stofan et.al 2016). This area has been associated with recently active volcanoes and coronae (Stofan et.al 2016). Themis Regio is a highland that is surrounded by plains and is the southernmost extension of the Parga Chasmata (Stofan, 2012). The elevation of this area is 0.5km and the rise of this area is mainly due to the Coronae, which is surrounded by fracture that have been filled with lava deposits (Stofan, 2012). This makes this a unique and variable area which allows the testing of the tool on a very specific and unique environment.

These areas were chosen as they vary significantly to the radar images used to train the model and around which the tool was designed, thus by producing results for these six locations, it will be possible to assess how applicable the tool is for generating images across the planet.

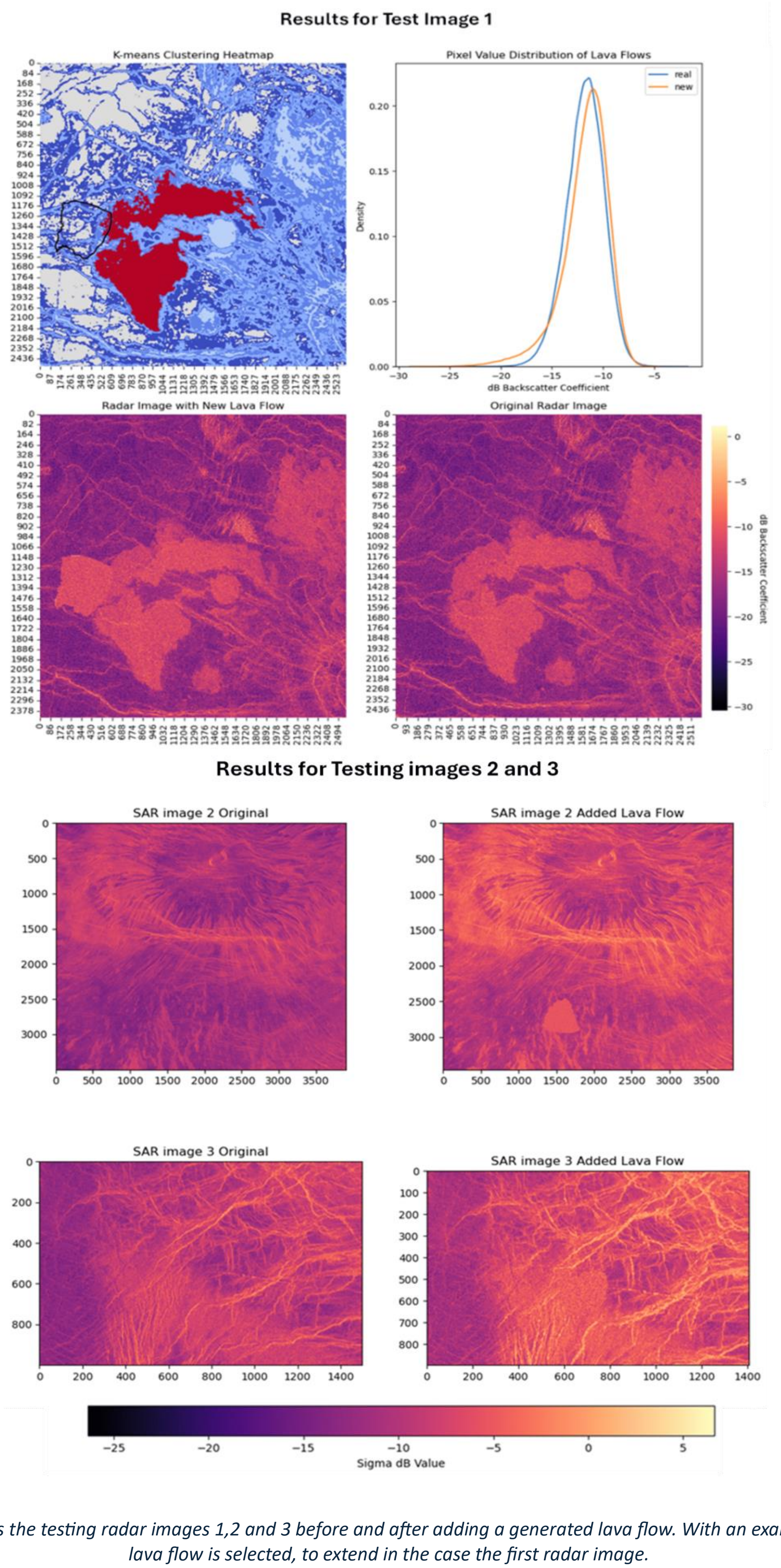

Figure 7 Shows the testing radar images 1,2 and 3 before and after adding a generated lava flow. With an example of how a lava flow is selected, to extend in the case the first radar image.

The results from test image 1, which is shown in figure 7, is an example of the extension of a lava flow that is highlighted in the K-means clustering heatmap.

From this it is clear that the tool is successful in selecting a lava flow, as the highlighted lava flow matches the outline of the lava flow in the original image, thus suggesting that the segmentation method is accurate enough for this task. For test images 1 and 3 the generated lava flow does not look like a perfectly natural extended lava flow, as there are clear fissures across the area in which the lava flow cannot replicate in the image, making it look out of place. However the actual texture of the lava flows does match well.

For test image 2 however, the generated lava flow is clearly visible and does not seem to match the actual surrounding area. This is most likely do to the fact that the landscape in this radar image is too different to the ones that the tool was created on. Image 2 has high levels of sudden variations in the backscatter coefficient which is a characteristic unlike the data that the tool was trained on.

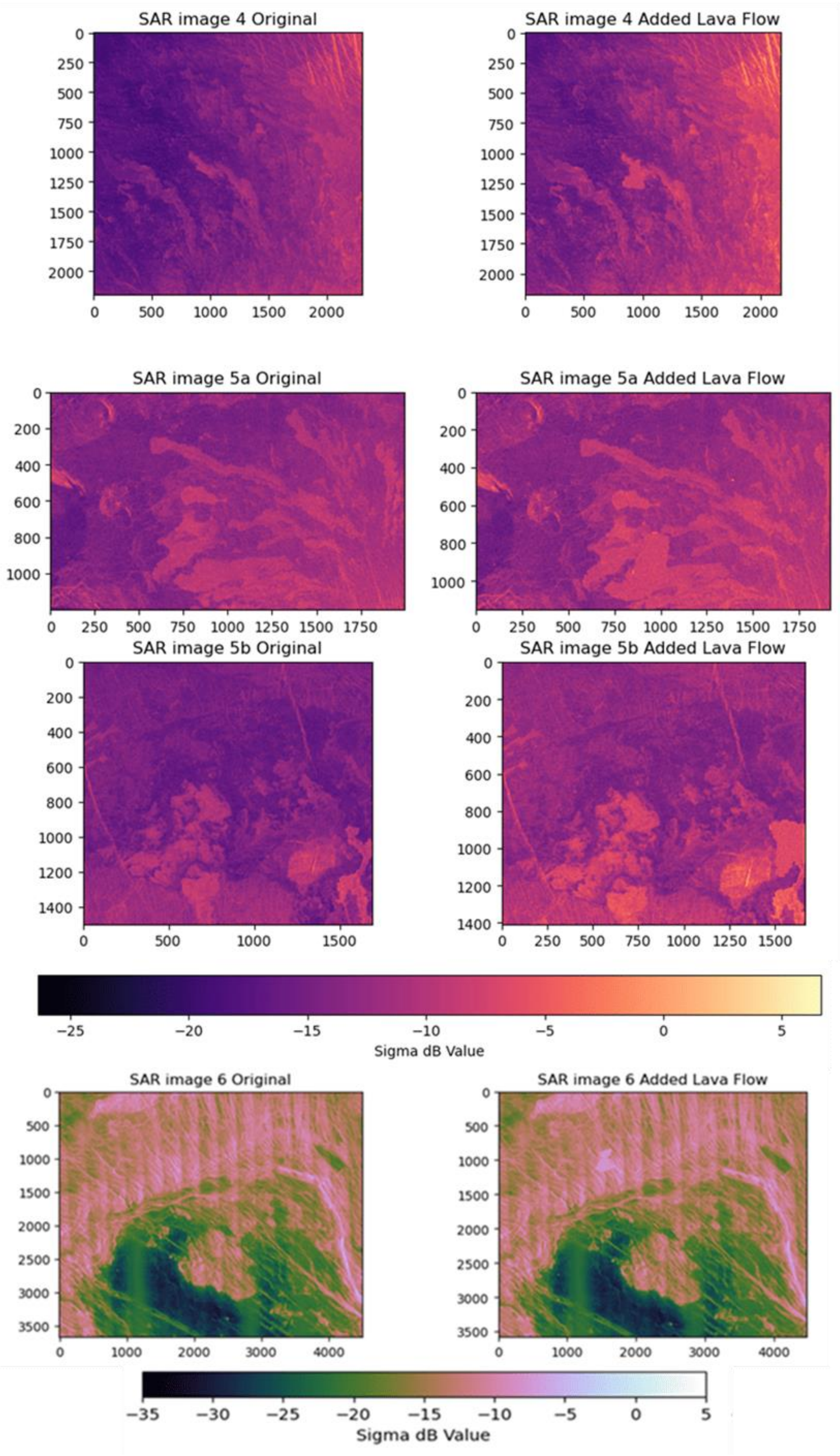

Figure 8 Shows the testing radar images 4,5a, 5b and 6 before and after adding a generated lava flow.

As shown in figure 8, where two radar images were taken from location 5, and one from 4, the lava generation tool was most successful at these locations. This is most likely due to the Thermis Regio region, in which 4 and 5 are located, having significant volcanism, thus the landscape is already abundant in lava flows.

Overall, the area has similar landscapes in the radar images that were used to create the tool. For image 6 the synthetic lava flow is very evident in figure 8, as the tool is not designed to work well in locations that have dynamic changes in backscatter. This an issue specifically related to the mechanics of the tool, as the mean backscatter is chosen by finding a segment of the image with a consistent backscatter coefficient. However with an image like image 6, the areas of consistent backscatter is very small thus will not produce a reliable mean and standard deviation as it is chosen on a small sample set, this is reflected in the ENL values depicted in figure 10 as the ENL of the original image is significantly lower than the generated lava flow.

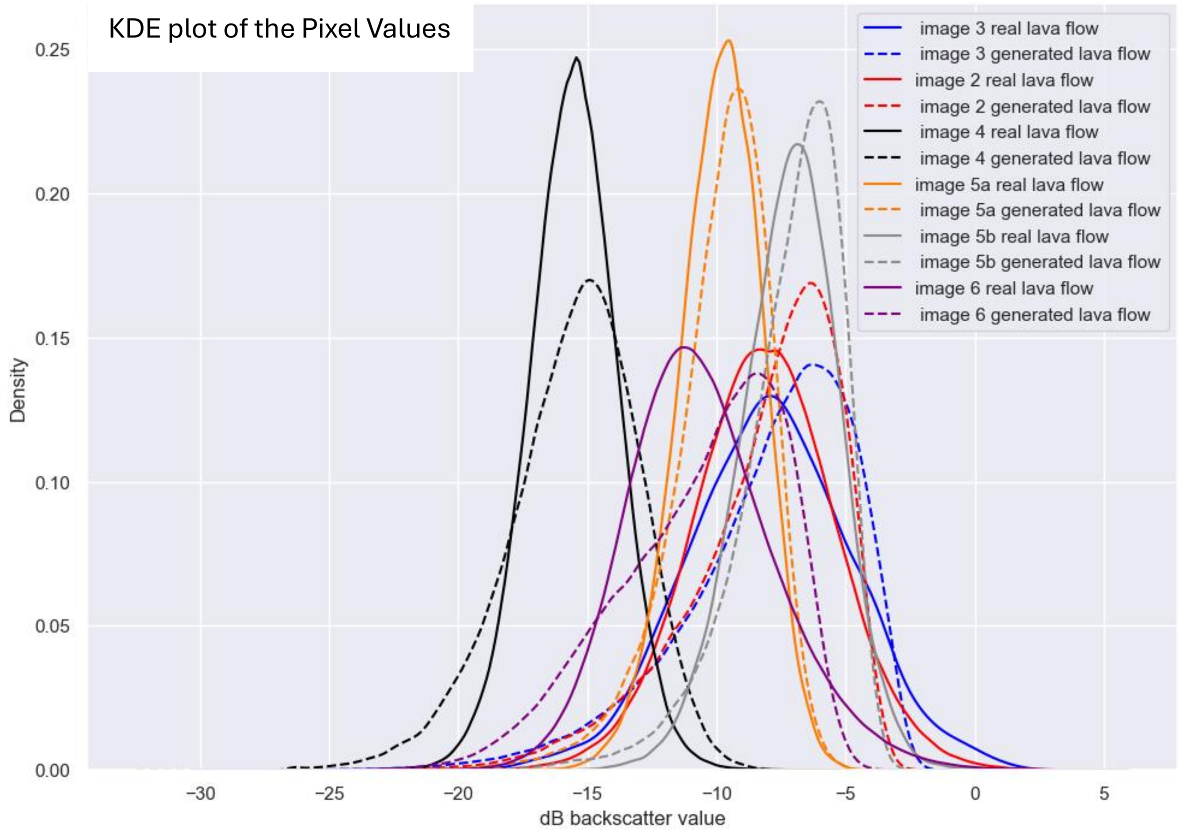

Figure 9 depicted the distribution of the pixel values of the real lava flows and the synthetic ones, for each image used to test the tool.

Image Number	ENL of Original (Real) Lava Flow	ENL of Generated Lava Flow
1	**5.4**	**6.1**
2	**4.6**	**6.1**
3	**4.6**	**3.0**
4	**6.7**	**5**
5a	**7.6**	**7.3**
5b	**2.5**	**2.7**
6	**0.87**	**5.6**

Figure 70 table of the ENL values of one of the real lava flows in the test images, as well as the calculated ENL of the Generated Lava Flow.

The ENL of the original lava flow and the generated are very similar in most cases, suggesting that the level of noise has been kept consistent whilst producing the new lava flows. The outlier is in image 6 where the ENL of the real image is so low, the level of noise must be very high, whereas the generated image has a more consistent level of noise, maybe if the speckle noise was increased for this image it would give an ENL value similar to the original image.

The KDE plot compares the pixel value distribution of the real lava flows and generated flows. Overall, for each image the distribution is very similar, however there is a trend of the generated lava flows leaning more towards the higher values in comparison to the real lava flows, thus leading to the generated images to look generally slightly brighter. This could be fixed by improving the method of texture generation.

Discussion

One of the more challenging tasks has been creating the texture as it is a difficult to find a simple way of quantifying it. Originally a diffusion model was used to replicate the texture, however this was not effective as the images did not look realistic and, more importantly, the generation of the images took too long. The model was designed to produce 28x28 tiles to create a lava flow at a reasonable size. However a normal size of a lava flow is usually 100s of kilometres (Roth and Wall, 1995) so there would need to be at least 50 tiles generated to make a lava flow roughly the size of $100km^2$, however to generate a batch of eight would take an hour to run. This was a big problem which led the project towards using a GAN model. This is able to produce images faster as the mechanics are not iterating multiple times per image to denoise them to produce results.

Furthermore, it was challenging creating a shape to represent the lava flow as the shape was supposed to be randomly generated on the radar image, where the size and location on the image are inputted. However, producing a completely random polygon created a very unrealistic looking image, as lava flows are often a more rounded shape . To take this into account, a Bezier curve function was implemented to create roundness in the shape, however this produced a shape that was very smooth and unnatural-looking, thus a noise that causes fluctuations in the shape's boundary was added. A Perlin noise algorithm was integrated into the Bezier curve function to produce this round but randomly fluctuating shape for the lava.

One of the strengths of the solution is that the whole tool runs relatively fast as the generative model can produce the texture quickly. Which means that it can be used for radar images that are large in size. In addition the final results produce images that are visually indistinguishable from real lava flows.

Generating the Texture

The task of replicating the texture, took a level of trial and error to be able to do this successfully. Due to the complexity of this task, there is still room to develop this further. As the task of creating a Deep learning model that can produce the best replication of a lava texture could be a project on its own, as there are many different models that could be used and compared to find the best one. For example, one of the drawbacks of a GAN model is its lack of diversity, resulting in texture tiles that look very similar. Therefore, if this project was extended, it would be interesting to try some other model architectures that might be able to have the same efficiency and accuracy as the GAN model but also have more diversity in the generated images.

Originally, a diffusion model was used to generate the images, however the model works but iterating multiple times to denoise an image of noise thus it is very time-consuming and inefficient in generating new texture for the lava flows. On the other hand, the GAN model could produce images rapidly. However the model structure and architecture used is a relatively simple GAN, specifically a GAN with deep convolutional layers (DCGAN). There has been plenty of research on the generation of radar images with synthetic images, and variations on the GAN model is a common approach to generating these images. So it could be beneficial to explore the different architectures used in these other research papers and see if they would be effective in producing the texture of lava flows on Venus.

Segmenting the Lava flows /Backscatter

To find the right backscatter coefficient required knowing the mean backscatter of lava flows already in that area. This leads into the first task of this project: detecting lava flows to get a mean backscatter value. The method in which the lava flows were segmented is not scientifically correct as there are many more nuances in how different morphologies are represented by the backscatter coefficient. This is because the interpretation of SAR backscatter for volcanology is challenging as there is no simple relationship between the magnitude, or sign of backscatter change and the physical properties of fresh volcanic deposits (Dualeh, 2021). Variables such as local slope and dielectric properties also affect the scattering properties of the ground surface (Abady et.al. 2022). However, for this practical use, separating the image by the backscatter mean works for this application as it is an intermediate step.

Suggestions for Future Research

The next step would be to improve on the shape of the synthetic lava flow, as currently the shape is created pseudo-randomly, however it would make sense for the lava flows shape to be impacted by the landscape beneath it, including the topography. With the topography it would be possible to model the flow direction and create a realistic image. In addition, incorporating information related to the position of the satellite during detection into training the model could improve the quality of the images produced (Abady et.al. 2022). As well as other custom data spanning from land-cover information to digital elevation models providing altitude details (Abady et.al. 2022). By providing metadata to the model, it will then be able to generate an image that is coherent with a set of imposed metadata in terms of geo-location and pixel elevation and this might increase the quality and plausibility of the synthetic images (Abady et.al. 2022).

One of the big challenges in generating synthetic SAR images is the clutter and speckle noise that is associated with SAR data (Guo et.al. 2017). There has been research to cope with this issue, in the form of clutter normalization method, which aims to reduce the influence of clutter (Guo et.al. 2017) . This would be an interesting method to explore in the context of recreating the lava texture in the Magellan radar images.

Overall, one of the main limitations to achieve realistic synthetic SAR images is that the image has to be created as tiles that are mosaiced together, as GANs cannot handle images larger than 256 × 256 very well. So only texture that can be captured in pixels at a maximum size of 256x256 can be learnt by a GAN model. Furthermore most generative models cannot manage image patches larger than a resolution of 512×512 pixels (Abady et.al. 2022). This, in the context of satellite data, is quite a limiting factor, though this restriction is expected to be surmounted in the near future (Guo et.al. 2017).

Conclusion

Overall, this project has been successful in producing realistic looking lava flows, the tool is also efficient and allows a lot of customising thus can be adapted to different types of radar images. There are areas in which this project could be taken further, such as improving the texture generated by the deep learning model. It is important to address the implications of research in this field. This research could assist in understanding the volcanism on the surface of Venus, as well as how radar imagery can be applied to the exploration of Venusian geology. Especially as there is the planned Envision and VERITAS missions in the next decade which will significantly increase the available radar images of Venus, meaning there could be more applications for the tool designed in this project.

However, it is important to acknowledge the issues that could arise with this area of research, as being able to change and adapt Radar images could be linked to creating synthetic forgeries of satellite images (Abady et.al. 2022).

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