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MACHINE LEARNING FOR BARCHAN DUNE DETECTION

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Barchan dunes are commonly found on the surface of planets such as Earth and Mars, playing an important role in the evolution of landscapes and ecosystems. Over the last few decades, imagery from remote sensing has been a valuable tool for investigating the morphodynamics of barchans, but their complex interactions and transformations make them sometimes difficult to be detected. In this study, we use the capabilities of Artificial Intelligence (AI) and neural networks to develop an accurate and efficient model for detecting dunes formed in an experimental rectangular channel. First, we collected a dataset of barchan images that we used to train and evaluate the accuracy of our model, based on convolutional neural network (You Only Look Once-YOLO) method, which can can accurately determine if an image contains dunes with an efficient success rate. We processed the images and data in Python using some of its libraries such as tensor flow, keras, opencv, numpy, pandas, etc. Next, we created a database to store and organize tagged images, and then compute the main results from the automatic detection of dunes such as dimensions, shapes and other properties of barchan dunes. From this technique, the dataset obtained in this study can be used for further studies and applications related to dune detection in remote locations, providing a valuable resource for researchers. Overall, our research shows the potential of artificial intelligence and neural networks in the fields of Physics and Geoscience, and how they can be used to overcome the challenges of studying complex natural phenomena on Earth and on other celestial bodies. The ability to accurately identify and study dunes using AI can improve our understanding of surface processes that are important to shape our landscape. We plan to continue investigating the possibilities to use Artificial Intelligence in other types of dunes and natural formations.

Keywords: *Barchane dune, Artificial Intelligence, YOLO.*

1. INTRODUCTION

Barchan dunes are sandy geological formations found in deserts, semideserts, and on the surface of celestial bodies such as Mars. In general, they are found in regions with predominantly unidirectional flow and a limited amount of grains (Bagnold, 1941). Barchan dunes have a crescent shape with a high crest and steep slopes on both sides known as horns. There are formed through interactions between the imposed flow, multitude of particles, and collisions among them (Hersen and Douady, 2005).

In order to better understand the dynamics of barchan fields, different techiniques were employed for the identification and measurement of barchans. However, these methods still require manual extraction of data obtained in the field or from images (van der Merwe *et al.*, 2022). In addition, Previous studies, such as those by Norris (1966), Bagnold (1941), Hugenholtz and Barchyn (2012) state that this type of fieldwork is expensive and time-consuming, since such observations, cannot bring complete information of the interactions of the barchans, due to the timescale (of the order of decades for eolian dunes).

For this reason, Alvarez and Franklin (2017)carried out controlled experiments with underwater dunes, allowing the time and length scales to be reduced from decades and kilometers to minutes and centimeters. Also, in order to better understand the physics involved, experiments with binary barchan interactions in both aligned and off-centered dune positions were proposed. For example, Assis and Franklin (2020) carried out experiments in which they investigated the variations in initial separation, alignment, dune mass, flow velocity and particle type. Understanding the complex dynamics of the dual relationships between subaquatic barchans is essential for understanding the behavior of those dunes. Assis and Franklin (2020) linked five distinct double trade patterns: chasing, merging, exchange, fragmentation-chasing and fragmentation-exchange. This interactions can be seen in the Figure 1.

Overall, in this work, in order to analyse the morphology of the Barchan dunes and to complement the studies carried out by Assis and Franklin, we work with the scheme shown in Figure 2. Therefore, the parameters to be analysed are: length *(L)*, width *(W)* and length of the two horns *(La e Lb)* (Moosavi *et al.*, 2014). For this reason, in the present work, these parameters were analysed over time. This was done in order to understand the morphology of the barchan dunes.

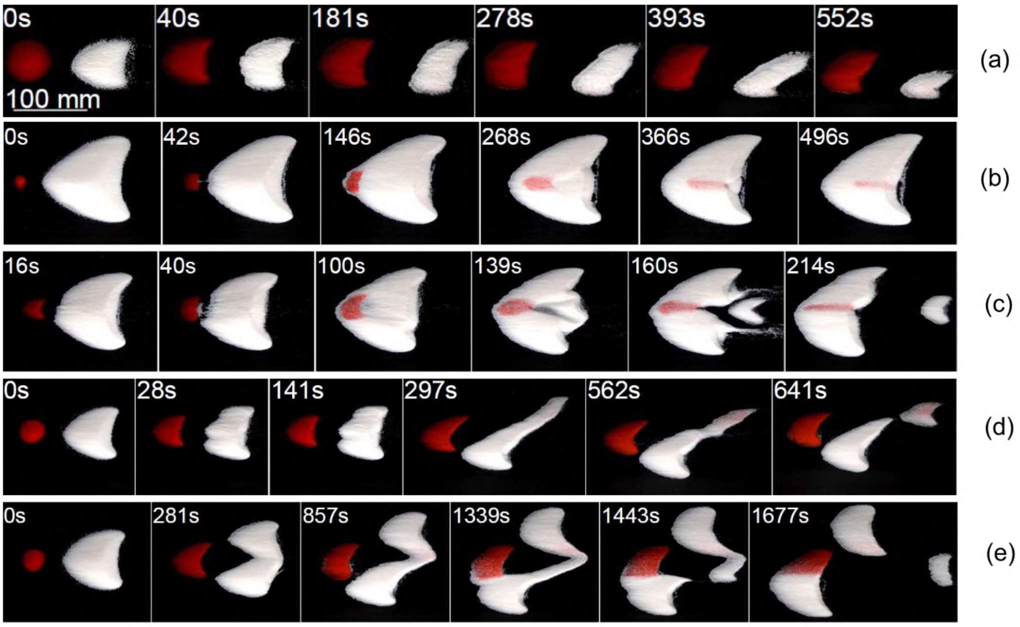


Figure 1: Barchan interaction for aligned dunes. (a) Chasing. (b) Merging. (c) Exchange. (d) Fragmentation-chasing. (e)Fragmentation-exchange. (Assis and Franklin, 2020)

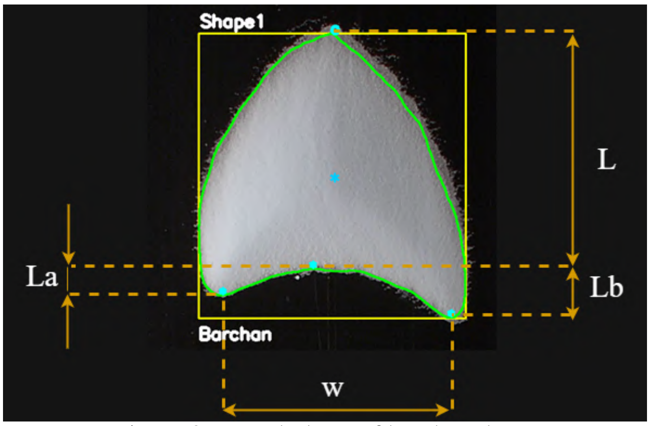


Figure 2: Morphology of barchan dune.

According to Deepika *et al.* (2017), artificial intelligence is a theory that is used to develop a system that can perform activities with the same intelligence as humans. The use of (AI) allows the development of expert systems for the detection of objects to extract information that can be used in research. In the last decade, artificial networks have revolutionized the detection of personalized objects in images. Rubanenko *et al.* (2021) detected Barchan dunes on Mars and Earth using the Raining Mask R-CNN method with accuracies ranging from 50% to 77%. That study focuses on the detection of isolated barchan dunes, and to build a database for training, dune field images were extracted from the global CTX mosaic.

On the other hand, Wong *et al.* (2019) reviewed that object detection stems from modern advances that are lead to increasingly complex object detection using networks such as SSD, R-CNN, Mask R-CNN, and other extended variants. However, to meet the challenge of object detection, there has been a growing interest in the research and design of highly efficient deep neural network architectures, one of which is the *YOLO* (You Only Look Once) network. According to Wang *et al.* (2022), this network significantly reduces model sizes, improves detection performance, making it much faster than other neural networks. Generally, they used a multi-scale method for training and the Darknet method, which is a network pre-trained on ImageNet. For this reason, in the In the current work, *YOLO* has been used to train the neural network.

Overall, our research demonstrates the promise of AI and neural networks in the physics and geoscience disciplines. We have successfully employed advanced technique such as *YOLO* with morphological dunes analysis. These methods have given us remarkably accurate detection and predict some patterns of barchan dunes. We seek to better understand the surface processes that are crucial in generating our landscape by using AI. to learn more about how different kinds of dunes and natural formations originate and change over time.

2. METHODOLOGY

2.1 Experimental setup

The experimental setup consisted a water reservoir, two centrifugal pumps, a supply tank, a return line assembly, and a 5 m closed hydraulic channel with a rectangular cross section made of transparent material and measuring (width = 160 mm and height = 50mm = 2δ). The above-mentioned order is followed by the flow, which is propelled by the pressure created by the pumps. To ensure a fully developed flow, the test segment is 40 hydraulic diameters from the channel's beginning and 1 meter long. Controlled grains were introduced to the test part of the channel after it had entirely filled with water, generating a pair of conical stacks in both aligned and center-off orientations. When flow is applied, each stack of particles deforms to form barchans, and they begin to interact with each other (Assis and Franklin, 2020). A total of 20 experimental runs were performed at the particle scale, covering 5 different types of binary interactions, which provided a database for the artificial intelligence training described in Section 1. The graphical scheme of the experimental setup is shown in Figure 3 and Figure 4 shows the experimental setup and the top view of the experiment.

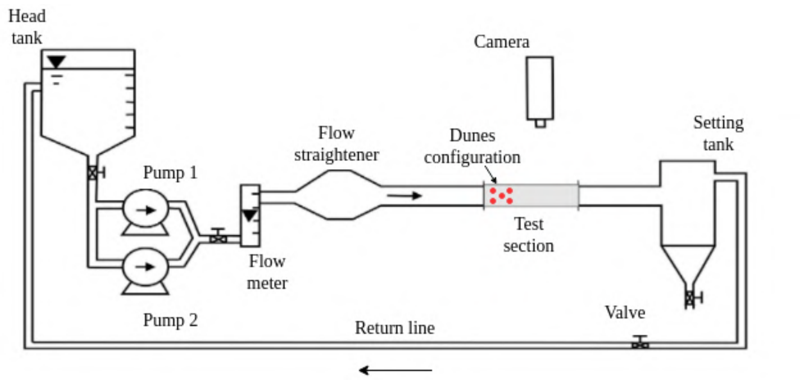
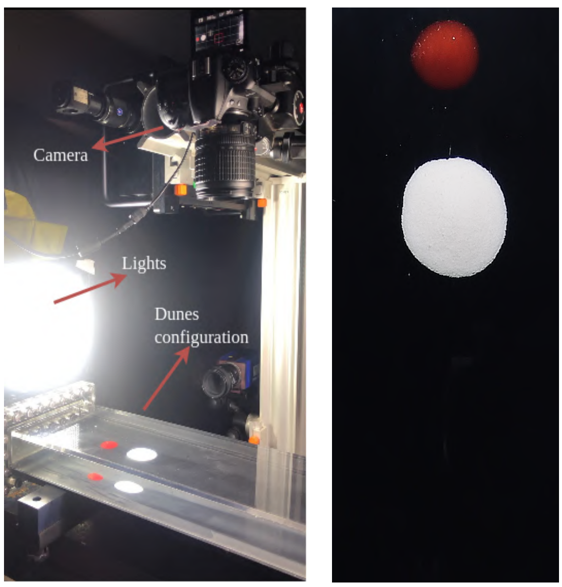


Figure 3: Schematic of the experimental setup. Figure modified from Assis and Franklin (2021).

The hydraulic channel water surface temperature during the testing ranged from 26°C to 28°C, while the ambient air temperature hovered at 27°C. Round glass particles (ρ_s = 2500kg/m^3) with diameters of 0.15 mm $\leq$ d $\leq$ 0.25 mm and 0.40 mm $\leq$ d $\leq$ 0.60 mm were employed for the development of the current study together with other grains (unmixed and different colors). Mean flow velocities ranged from 0.243 to 0.278 m/s, corresponding to channel height-dependent Reynolds numbers Re = $\rho U 2\delta/u$ within $1.22 \cdot 10^4$ and $1.39 \cdot 10^4$, where the fluid's density is ρ and the dynamic viscosity is u. A traditional camera with a high resolution of 1920 px X 1090 px and a frequency of 60 Hz was mounted on the traverse system put on top, as illustrated in Figure 4, to capture the evolution of the dunes. Finally, each test's experimental portion lasted roughly 10 minutes, during which time an ideal database was created for the neural network's training.

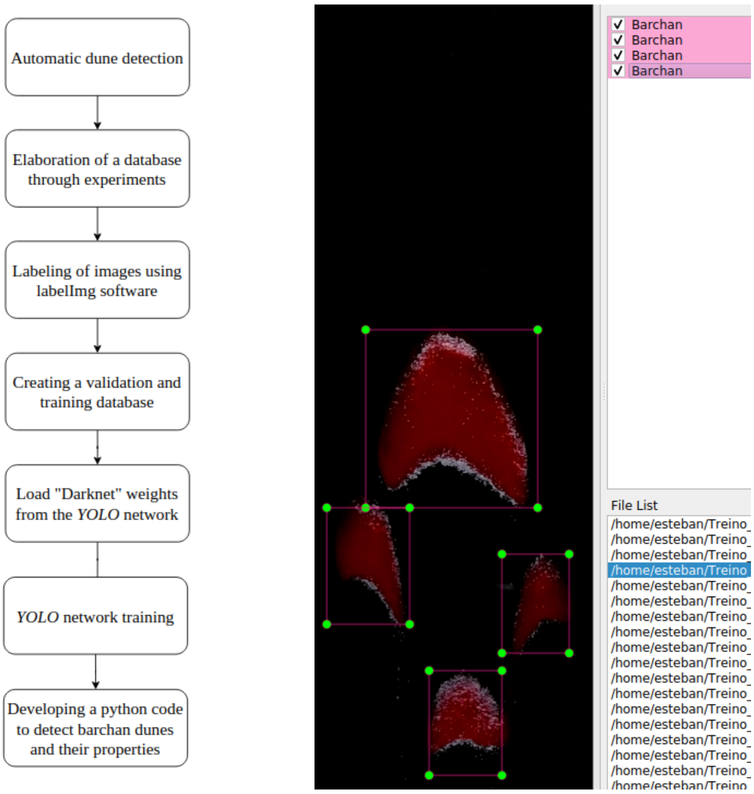


(a) (b)

Figure 4: (a) Experimental setup. (b) Top view of experiment

2.2 Automatic dune detection

For the automatic dune detection, the following steps were taken sequentially. First, a large database of experimental data was constructed, taking into account binary interactions from previous work. Next, around 4500 images were labeled using the labelImg software. A validation and training database was then created using the labeled images. Next, the darknet weights were loaded from the *YOLO*. This network was trained using the labeled database with a total of 300 epochs, a batch number of 7, and a batch size of 654. During training, two layers were specifically trained, one to detect Barchan dunes (Barchan) and the other to detect non-Barchan regions (Not a barchan). Finally, a Python code was developed to run the trained model, detect Barchan dunes, and analyze their morphology. Automatic detection is detailed in Figure 5a and image labeling is shown in Figure 5b.



(a) (b)

Figure 5: (a) Steps to developed a *YOLO* network. (b) Labeled for a four-dune configuration.

Overall, for the development of the morphology study, Python packages such as Flow Tensor, Keras, Pytorch, Opencv and other libraries were used to draw the contours and obtain the results presented in the section 3. For this purpose, different filters such as join masks, median blur, kernel and morphology were used and image processing were applied to identify and delineate the surfaces of the Barchan dunes. The points of interest for the study of their morphology were traced and analyzed as a function of time. Having results such as their displacement, variation of their length and width over time for further studies to calculate the physical parameters involved in the process of dune formation.

On the other hand, it is necessary to mention that the training parameters were chosen based on the characteristics of the available computer. These characteristics are an Intel Core i9 processor, an RTX 2070 graphics card, a 512 GB SDD, and two 4T internal HDDs. It is recommended to work with this type of process in conjunction with the computer's GPU to obtain better technical performance, which requires Nvidia packages (CUDA 11.5 and cudnn toolkits 8.8.0) compatible with the mentioned GPU.

3. RESULTS AND DISCUSSION

In this section we present the results of the automatic dune detection. In Figure 6 we can observe the losses as a function of the epochs on the model trained with the YOLO network. In this Figure, we can see that the model starts to converge from epoch 150 and a loss value of 0.40, this result indicates that the next trainings could be run for up to 200 epochs without losing confidence in the results. Moreover, the training has a recognition confidence of more than 90% for each of the labels placed during the training.

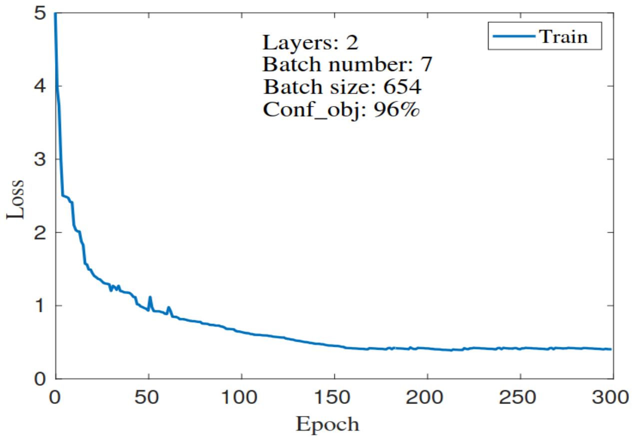


Figure 6: Model loss.

In addition, in the present work we have chosen to present the results for two tracking binary interactions mentioned in the work of Assis and Franklin (2020). In Figure 7 we can see the tracking case for 2 dunes with a time interval of 50 seconds, while in Figure 8 we can see the same interaction for 5 dunes but with a longer time interval. From these figures we can see that the YOLO network provides an efficient automatic detection of the Barchan dunes with a detection interval of 95% to 98%. The main result is that the code is able to perform the extraction of the points of interest for the morphological analysis of the dunes. Moreover, it was observed that the filters and Python packages used allowed optimal results in the extraction of information about the morphology of the dunes. At this stage, the filters used were allowed to draw the contours of the images and obtain all the points on the surface of the dunes to analyze their morphology. The points that have been stored to perform this analysis have been detailed in the work of (Moosavi *et al.*, 2014) in section 1.

In this way, we analyzed parameters such as: the distance traveled as a function of the centroids on the y-axis, the length and width of the Barchan dunes, and the average distance of the horns due to the symmetry of the dunes in most cases. Moreover, these parameters will allow us to understand the physical phenomena involved in the binary interactions of the Barchan dunes in further studies. These results can be seen in figures 9 and 10, which will be explained below.

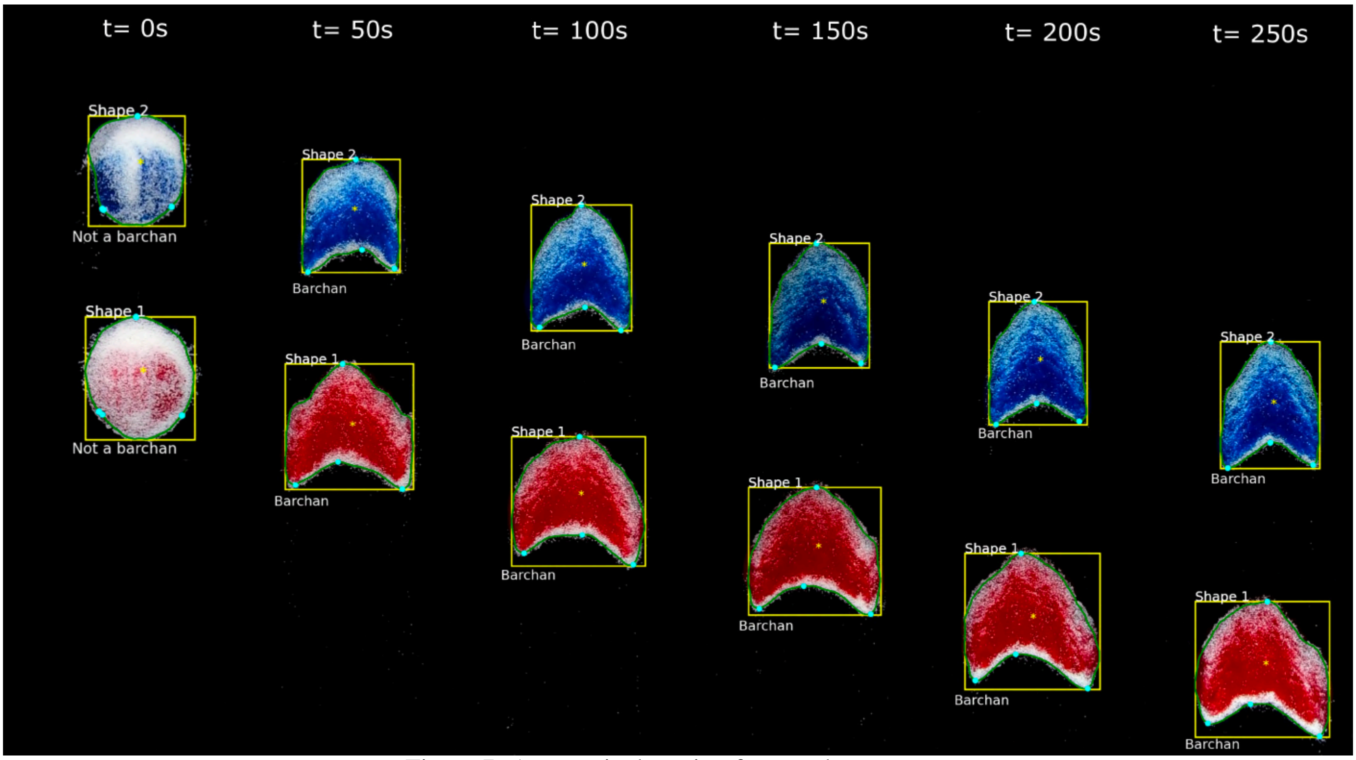


Figure 7: Automatic detection for two dunes.

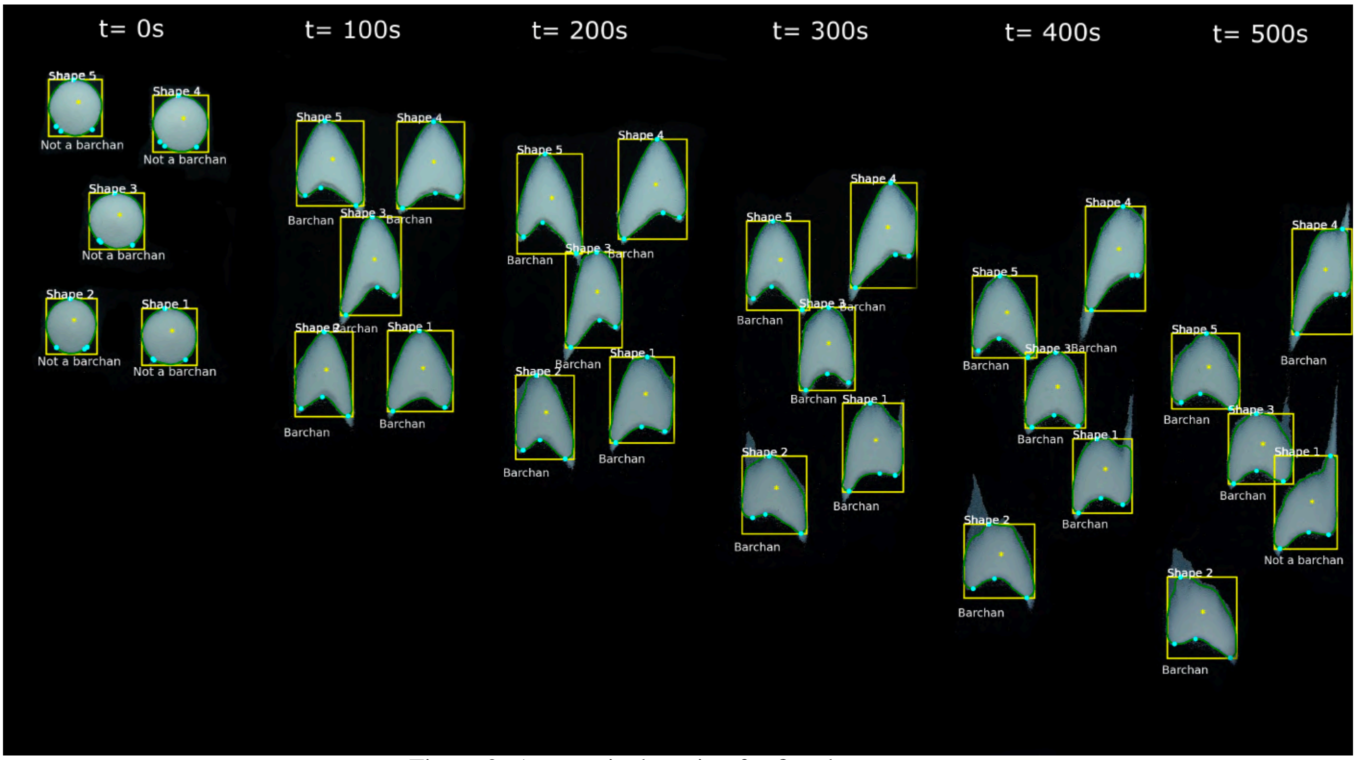


Figure 8: Automatic detection for five dunes

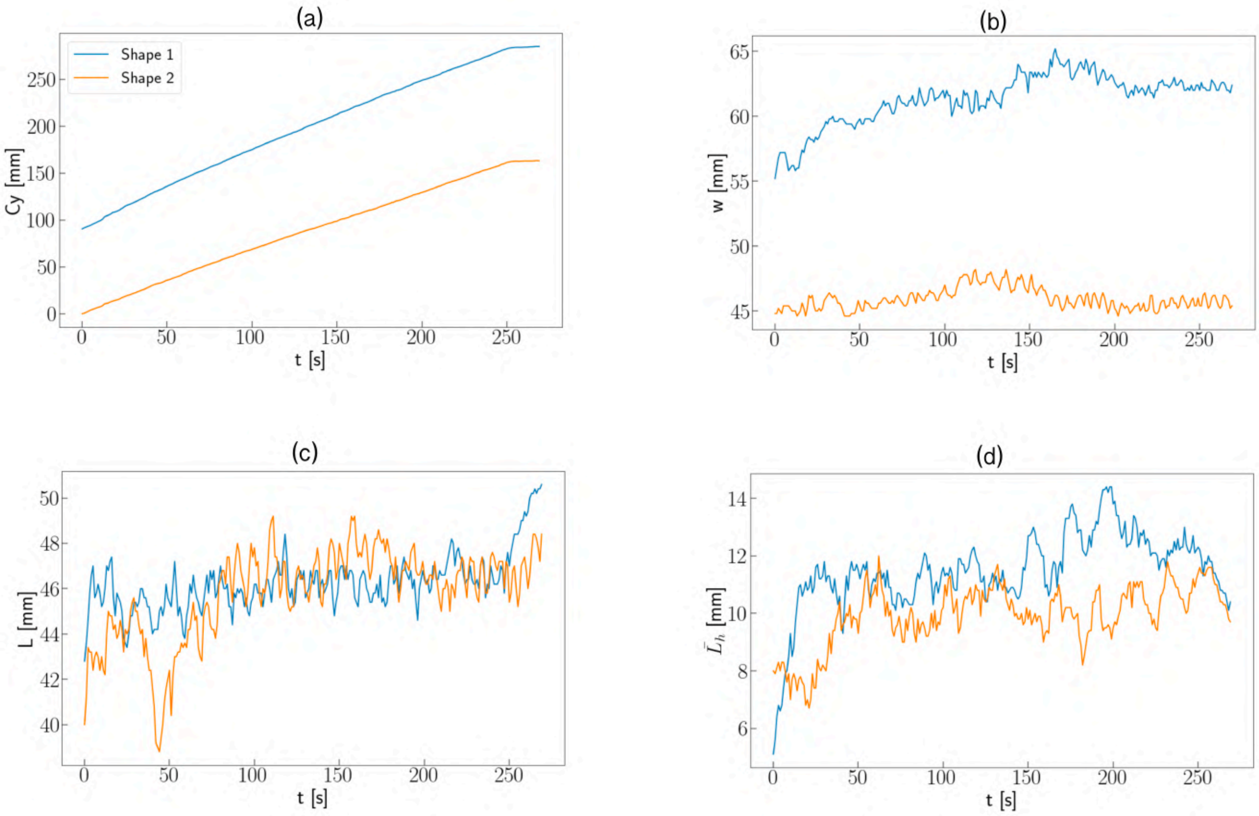


Figure 9: Results for the configuration of two barchan dunes. (a) Positions over time. (b) Width over time. (c) Length over time. (d) Average Lh over time

In Figures 9a and 10a it is possible to observe the positioning and movement of the Barcan dunes over time and to calculate several physical parameters such as acceleration. It can also be observed that between the two tests the dunes have different slopes and some even meet over time. This is related to the velocity of each of the Barchan dunes. Figures 9c and 10c show the behavior of the Barchan dunes in length, and figures 9b and 10b show the behavior in width. In these figures it can be observed that the results predict the behavior of the Barchan dunes when subjected to a constant flow. However, the tendency that these figures have is similar to a spring-mass system, which is an expected behavior for dune formation. On the other hand, it can be observed that figure 10c shows an increase in dune 5 because this dune leaned against a part of the experimental channel throughout the experiment. Finally, figures 9d and 10d show the mean value of the Barchan dune horns. The behavior of this parameter depends very much on how the glass grains or particles settle over time.

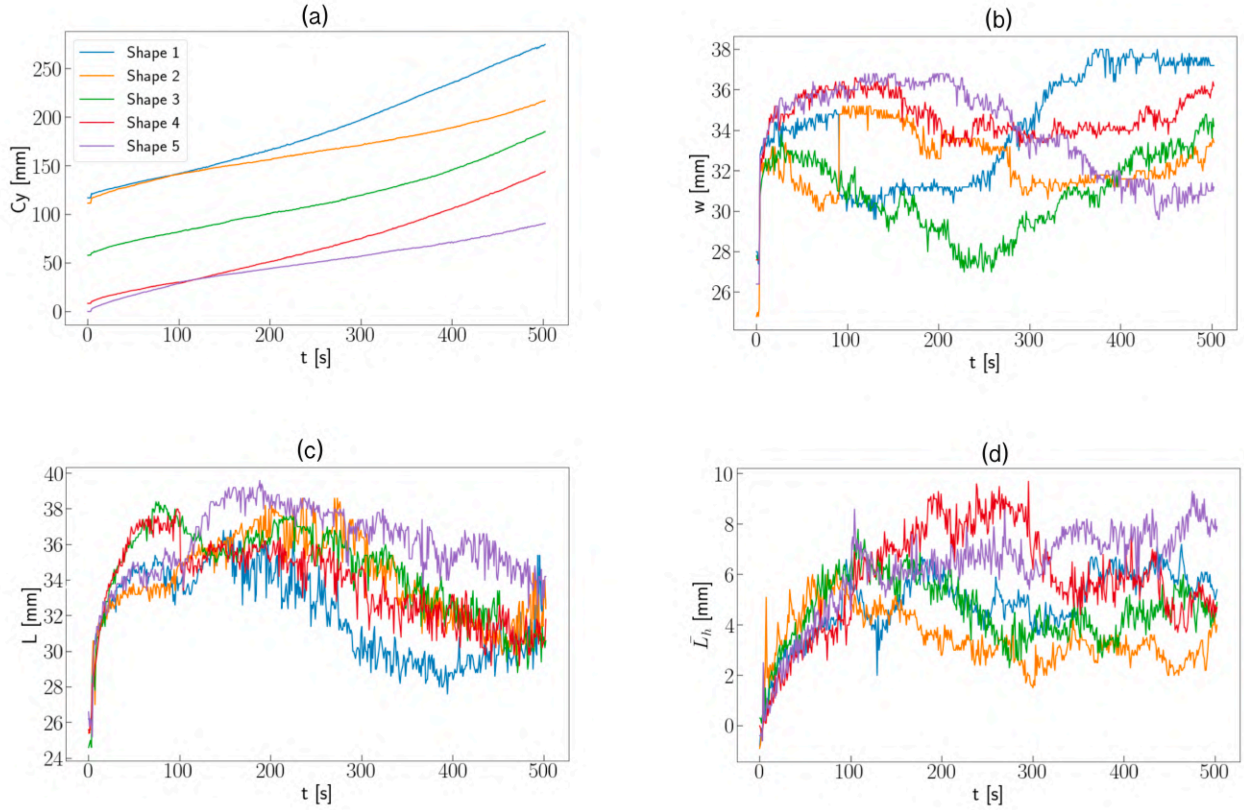


Figure 10: Results for the configuration of five barchan dunes. (a) Positions over time. (b) Width over time. (c) Length over time. (d) Average Lh over time

4. CONCLUSIONS

Overall, the automatic detection of Barchan dunes presents very efficient results in the detection of dunes. In addition, the physical parameters presented over time allow to focus more on the studies related to the physical part of the problem. On the other hand, the recognition reliability is above 95% in most cases, so that the number of epochs could be reduced in future trainings. However, the morphological analysis for the different binary interactions is still in progress, but in terms of dune detection it shows the same results as in the tracking case. Finally, it can be said that this work allows to identify and obtain the study parameters to efficiently understand the dynamic part of the dune interaction.

5. ACKNOWLEDGEMENTS

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