

 CONTENTS[Close](#)

Hello all, we at MathWorks, in collaboration with DrivenData, are excited to [Chimpact: Depth Estimation for Wildlife Conservation](#)

Through this challenge, you would get the real-world experience of working skills as well as win some prize money online, while working from home. You monitoring species population sizes and population change, which helps t

We encourage you to use MATLAB to train your model by providing [compl](#)

Your **goal in this challenge** is to automatically estimate the distance between camera trap videos. Automated distance estimation can rapidly accelerate conservation. The primary data consists of camera trap videos from two p and estimated bounding box coordinates for animals. Check out [this page](#)

For this **2 blog post series**, we will provide you with detailed resources that will talk about monocular depth estimation, working with videos as data so the problem with lowest error. [Second blog](#) is be a detailed starter code for

Monocular Depth Estimation

Monocular depth estimation is an inverse problem – given the resulting image features that make it up. Further to this, it is an ill-posed problem as there appears smaller in the image could just be further away, or vice versa. A g



Traditionally depth estimation is achieved through matching features across motion and stereo vision matching. However, in this example these approaches in the video, the displacement between frames is not known and so traditional methods are not applicable.

Despite the difficulties outlined above, monocular depth estimation is a well-studied problem in recent years. Hopefully, through this challenge, you can continue this progress.

Resources:

[Depth Estimation: Basics and Intuition](#)

Working with Data

Video data

Working with videos is an extension of traditional image processing – a video is a sequence of images arranged in a specific order. Each individual frame provides spatial information, and the dynamic nature of video offers an additional, temporal dimension.

The first step to consider is extracting the necessary frames from the video. These can then be processed before performing machine learning.

Resources:

[VideoReader](#)

[Image processing](#)

Processing Data

Another challenge in working with videos is the large size of the dataset. To create a repository for collections of data that are too large to fit in memory, you can store them in multiple files on a disk, a remote location, or a database as a single dataset.

Resources:

Understand the concept of datastore: [Getting Started with Datastore](#)

Create different datastore for images, text, audio, file etc. [Datastore for different](#)

Use built-in datastores directly as input for a deep learning network: [Datastores](#)

Implement a custom datastore for file-based data: [Develop Custom Datastore](#)

The data for the challenge will use the data stored in AWS. So, [Learn how to ac](#)

Getting started

Once the data is ready, the next step is to think about your approach. As with many challenges, there are many possible avenues to take here. The following paper provides a good starting point for different approaches and gives some ideas for further development: [Monocular Depth Estimation: A Survey](#). Further to this, we are providing below some starting pointers for

Method 1: Optical Flow + CNN

This first approach uses [optical flow](#) to detect the animals against the background. The output of the optical flow classification network to perform regression.

For each labelled frame in the videos, calculate the flow compared to the previous frame. If there is a stationary background, the optical flow highlights where they are and provides a measure of the signal to noise ratio, the provided bounding boxes is used to generate a new dataset of image frames to serve as input to the next step. Instead of simply cropping the images to retain spatial context.



This generates a new dataset of image frames to serve as input to the next step. Instead of simply cropping the images to retain spatial context, the optical flow highlights where they are and provides a measure of the signal to noise ratio, the provided bounding boxes is used to generate a new dataset and replacing the last few layers to perform regression down to a

In this method, whilst each input is considered in isolation, the optical flow video.

Resources:

To learn how to implement [Optical flow](#) using algorithms Horn-Schunck method, out this tutorial video: [Computer Vision Training, Motion Estimation](#)

[Deep Learning with Images](#)

Introduction to [Convolutional Neural Networks](#)

Method 2: Importing existing models to MATLAB

In their paper “[Digging Into Self-Supervised Monocular Depth Estimation](#)’ Monodepth2 for depth estimation off a single image. Their depth prediction produces a depth map for the scene. Additionally, they have provided the code that can be imported to MATLAB and retrained to our new scenario.

In order to import the PyTorch model into MATLAB, it first needs to be exported to [ONNX format](#). Fortunately, PyTorch provides a very simple workflow for this process.

You can also run the python script (“pytorchToOnnx.py”) we used for testing.

Once in ONNX format, these can be easily imported into MATLAB using the [MATLAB ONNX functions](#).

Resources:

[Import Pretrained Deep Learning Networks into MATLAB](#)

[Deep Learning Import, Export, and Customization](#)

[Get Started with Transfer Learning](#)

Next Steps

If you do not have a MATLAB license, start your preparation by requesting a [MATLAB license](#).

Stay tuned for further updates and in the [next blog](#) we will expand on the code and suggestions for further development.

Feel free to give your feedback or any questions you have in the comments.

mathworks.com

© 1994-2022 The MathWorks, Inc. MATLAB and Simulink are registered trademarks of The MathWorks, Inc. See [MATLAB and Simulink trademarks](#). Other product or brand names may be trademarks or registered trademarks of their respective holders.