# Food Volume Estimation

Using monocular depth estimation to estimate food volume in an input image.

## Method

### Depth Network Training

A depth estimation network is trained using monocular video sequences, as suggested by Godard et al.. The sequences used for this purpose are obtained from the EPIC-Kitchens dataset, which includes more than fifty hours of egocentric, food handling videos.

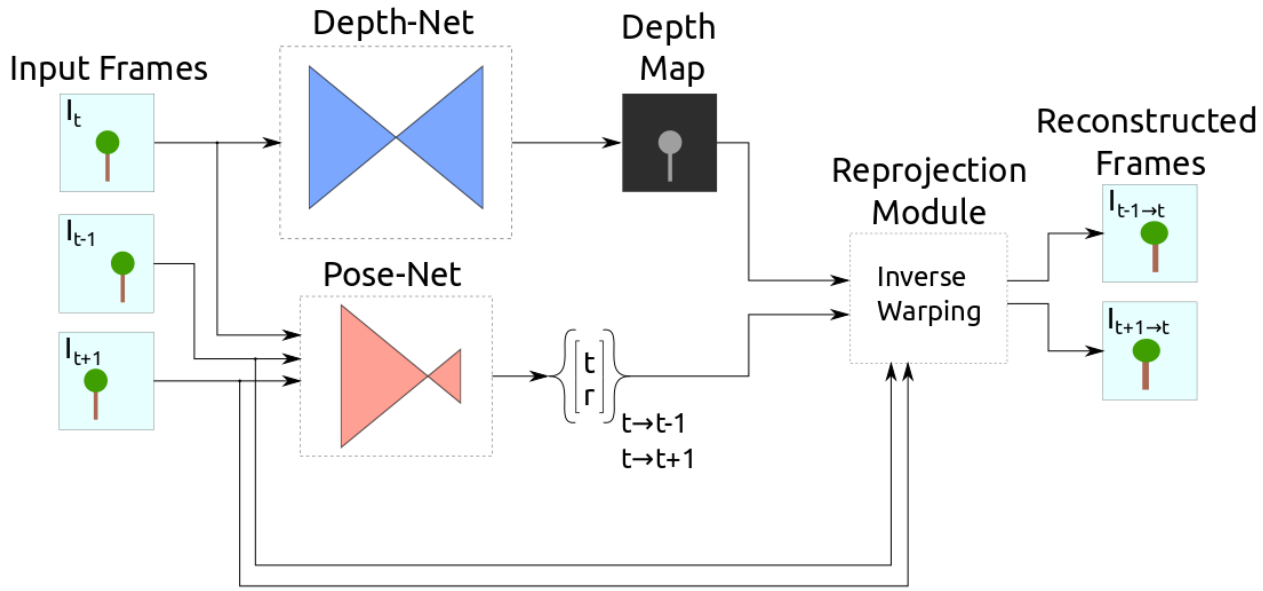



Figure 1: Depth Network Training

### Volume Estimation

The food input image is passed through the trained depth network and segmentation module to predict the depth map and food object mask. These outputs, along with the camera intrinsics, generate a point cloud on which the volume estimation is perfomed. When using images that depict a general kitchen scene, the food segmentation module may also include the plate in the segmentation mask. In such cases, the point cloud to volume algorithm can compensate the added error by using only an approximated filled portion of the whole plate, to avoid overestimating the food volume.

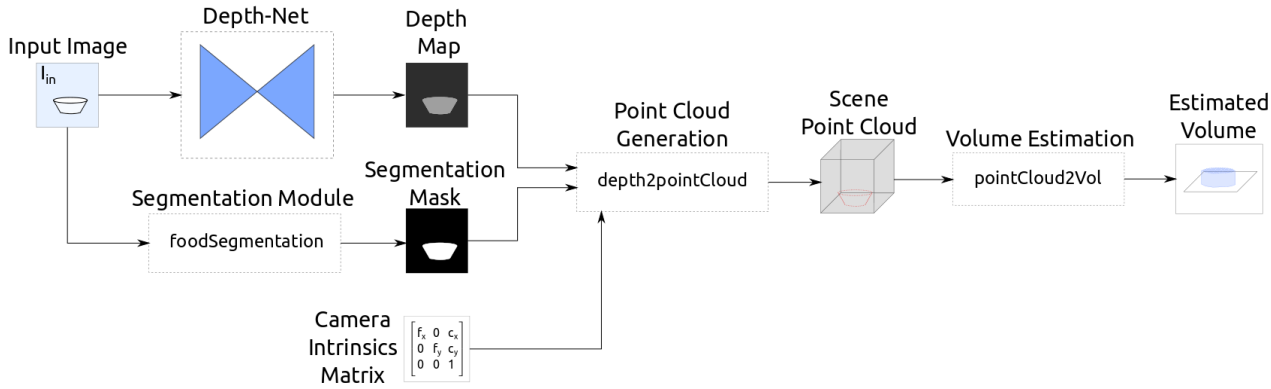



Figure 2: Volume Estimation

## Requirements

The code is written and tested in `python 3.6`. The required pip packages for running the volume estimation script are:

```
numpy==1.16.3
pandas=0.24.2
opencv-python==4.1.0.25
scipy==1.2.1
scikit-learn==0.21.1
tensorflow==1.13.1
keras==2.2.4
h5py==2.9.0
matplotlib==3.0.3
```

To train the model you also need `image-classifiers==0.2.1` for importing the required Resnet18 model and weights.

## Training

To train the depth estimation network use the `monovideo.py` script as:

```
monovideo.py --train --train_dataframe dataFrame.csv --config config.json
   --batch_size B --training_epochs E --model_name name --save_per S
   --starting_weights initial_weights.h5
```

The required arguments include a Pandas dataFrame (`dataframe.csv`) containing paths to frame triplets:

| curr_frame | prev_frame | next_frame |
|---|---|---|
| path_to_frame_t | path_to_frame_t-1 | path_to_frame_t+1 |
| path_to_frame_t+1 | path_to_frame_t | path_to_frame_t+2 |
| ... | ... | ... |

and a JSON file (`config.json`) that describes various training parameters:

```
{
  "name": "epic-kitchens",
  "img_size": [128, 224, 3],
  "intrinsics": [[1564.51, 0, 960], [0, 1564.51, 540], [0, 0, 1]],
  "depth_range": [0.01, 10]
}
```

The model architecture is saved in `name.json` when the model is instantiated whereas the model weights are saved in `name_weights_[epoch_e/final].h5` every `S` epochs and when training is complete (H5 format). All outputs are stored in the `trained_models` directory.
The triplet-defining dataFrame can be created using the `data_utils.py` script as:

```
data_utils.py --create_set_df --data_source data_sources --save_target df.csv --stride S
```

where the `data_sources` file contains the directories in which the images are saved. For example:

```
/home/usr/food_volume_estimation/datasets/EPIC_KITCHENS_2018/frames/rgb/train/P01/P03_3/
/home/usr/food_volume_estimation/datasets/EPIC_KITCHENS_2018/frames/rgb/train/P01/P05_1/
```

You can also create a training set from multiple EPIC-Kitchens source directories, resizing the images and applying optical flow filtering (proposed by Zhou et al.) to reduce overall training costs:

```
data_utils.py --create_EPIC_set --data_source data_sources --save_target save_dir
  --target_width W --target_height H --interp [nearest/bilinear/cubic] --stride S
```

To avoid redefining the data sources after creating and saving a training set of images, use the `create_dir_df` flag:

```
data_utils.py --create_dir_df --data_source img_dir --save_target df.csv --stride S
```

The recommended stride value for the EPIC-Kitchens dataset is 10.

## Testing

The `model_tests.py` script offers testing of either all network outputs or the full-scale predicted depth:

```
model_tests.py --test_outputs --test_dataframe test_df.csv --config config.json
   --model_architecture model_name.json --model_weights model_name_weights.h5 --n_tests 5
```

```
model_tests.py --infer_depth --test_dataframe test_df.csv --config config.json
   --model_architecture model_name.json --model_weights model_name_weights.h5 --n_tests 5
```

Again, a Pandas dataFrame defining the frame triplets is required, since the all-outputs test generates the source to target frame reconstructions. All tests are performed without data augmentation.

## Volume Estimation

To estimate the food volume in an input image use the `estimate_volume.py` script as:

```
estimate_volume.py --input_image img_path --depth_model_architecture model_name.json
   --depth_model_weights model_name_weights.h5 --segmentation_model [GAP/GMAP/GMP] --fov D
   --focal_length F --depth_rescaling R --min_depth min_d --max_depth max_d
   [--plot_results]
```

The model architecture and weights are generated by the training script, as discussed above. If either the camera field of view (FoV) or focal length is given, the intrinsics matrix is generated during runtime. Otherwise, a default 60 degrees FoV is used to generate the matrix. The depth rescaling, min depth and max depth parameters are model-dependent and should not be changed unless the model has been retrained with the new values.
If you wish to visualize the volume estimation pipeline, run the example notebook `visualize_volume_estimation.ipynb`. Point cloud plots are dependent on the PyntCloud library.

## Models

Download links for the pre-trained models:

- Low-res model:
  - → Architecture: https://drive.google.com/open?id=1IJ4k1TtFpConpkJVsGf37F-WWJ1rmP4Y
  - → Weights: https://drive.google.com/open?id=1mFvc20GbzUGyo9xl401BNxGNSLiKEewr

## Known Issues and Improvements

A list of observed issues along with proposed improvements is given below:

- The content of the training frames revolves around the general kitchen environment and not specifically food. Thus the granularity of the estimated depth on food surfaces is not as fine as the target objective requires, leading to rougher volume estimations. To solve this problem, the depth estimation network should be trained using videos focusing on food. However, food video datasets such as PFID have no camera motion (e.g., the food is placed on a rotating platter and the camera is stationary), which is critical to providing the network with a training signal.

- The depth network generates depth values corresponding to the scene depth range of the training frames. In order to correctly estimate the depth of an input image, with a different depth range than the one seen during training, the network output must be rescaled. In this implementation, the rescaling is done manually by multiplying the output with an approximation of the input median depth. Adding scenes with various scene depth ranges to the training dataset, could help in achieving this generalization property.
- The point cloud to volume algorithm finds a base plane on which the food is placed upon and calculates the volume contained between the plane and food surfaces. The fitted plane does not always match the actual plate, impairing the volume estimation. A potential improvement would be to fit pre-defined shapes on the generated point cloud, that can better approximate the contained volume and be more robust to noisy depth estimations.

## Examples

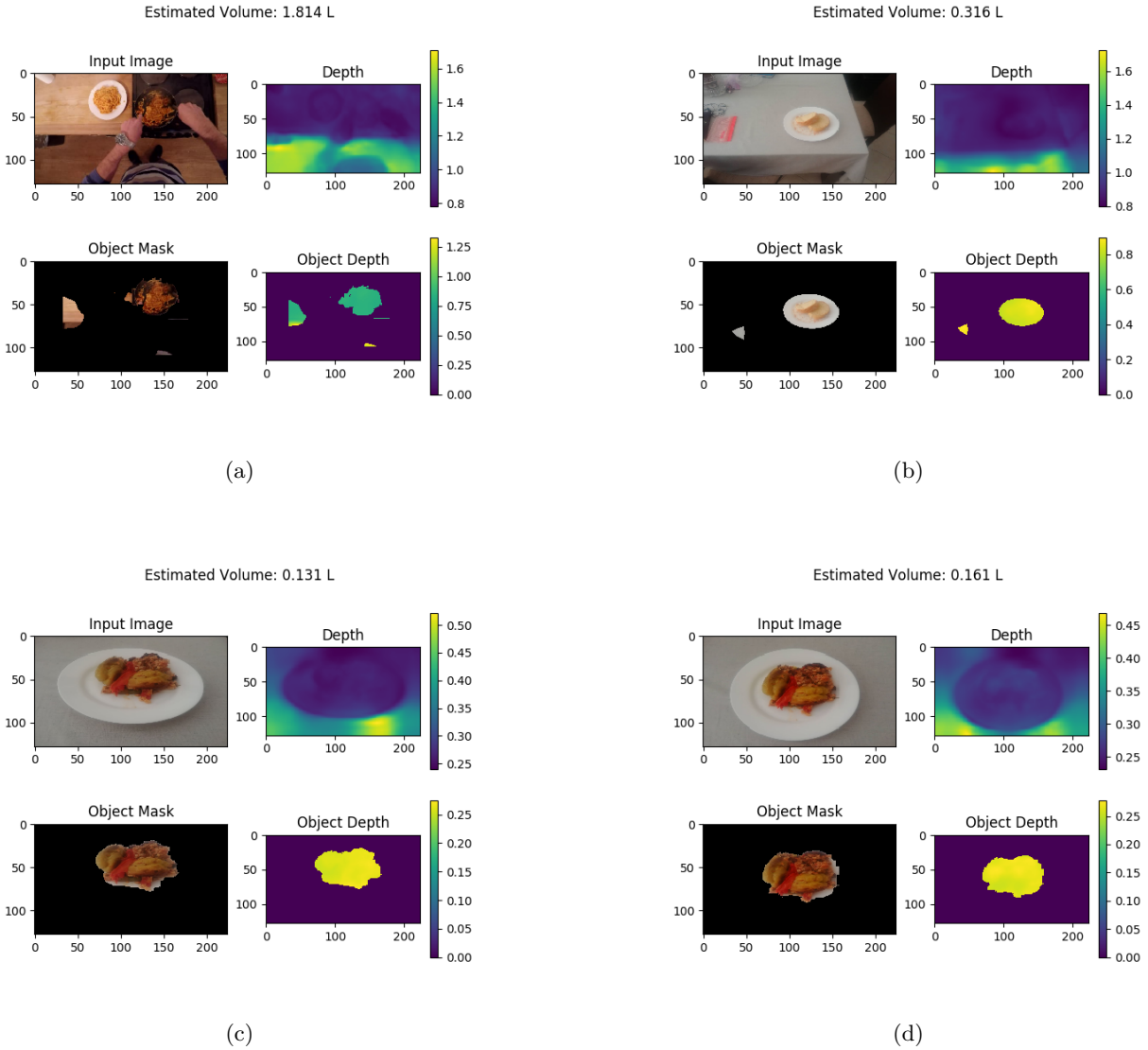
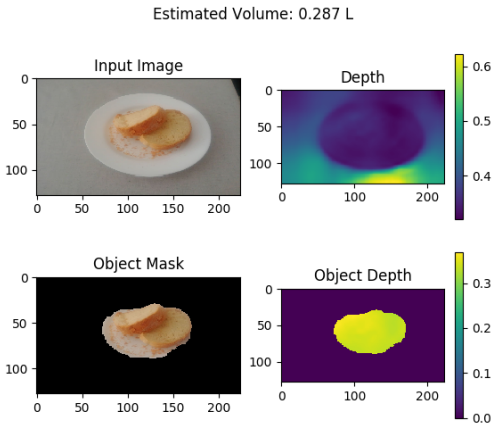
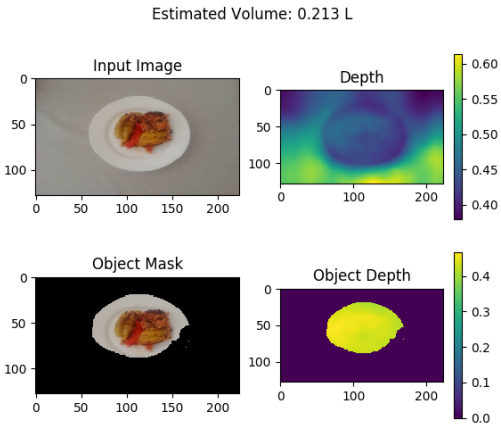


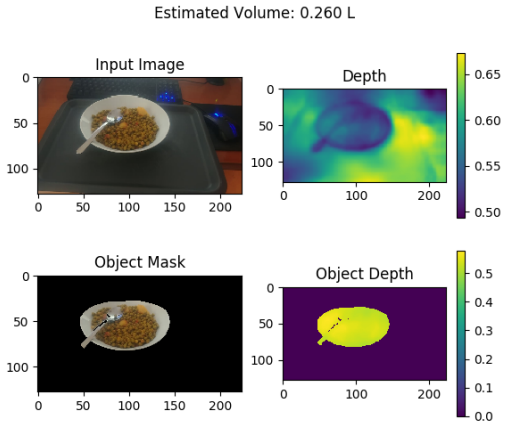

Figure 3: (a) **Example 1**: Using as input a frame from the training sequences, the depth network produces an accurate depth map. Having no clear food object in the scene, the segmentation module fails to generate a meaningful mask. (b) **Example 2**: Providing a similar scene to the ones seen during training, the depth network and segmentation module reproduce the results observed in Example 1. (c) **Example 3**: The given input is a close-up shot of a food portion on a plate. The depth network, being untrained on such scenes, cannot infer the fine depth details and instead produces a rough depth approximation. (d) **Example 4**: Similar to Example 3. In both cases, the depth map must be rescaled since the input image depth range differs from the ones seen during training.




(a)




(b)




(c)

Figure 4: (a) **Example 5**: Similar to Examples 3,4. (b) **Example 6**: As the camera moves further away from the food, the segmentation module includes portions of the plate in the generated mask. Applying the plate compensation algorithm reduces the added error. (c) **Example 7**: The created point cloud fails to capture the true depth of the plate, which is unobservable from the angle that the picture is taken from. This issue is inherent in estimating the volume from a single image.