Road markings detection and road measurement in aerial imagery

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***Abstract*—This report presents a method for road marking detection, more specifically using a segmentation approach. Our chosen method involves generating masks for the road markings. Utilizing the AU Drone Dataset, we obtained images depicting road lanes with markings, along with corresponding masks for each category or type of road marking. Presently, we are employing the UNet architecture to achieve image segmentation and train our model accordingly.**

***Index Terms*—Road Marking Detection, Segmentation, Aerial Imaginary.**

I. Introduction

Detecting road markings and measuring road features from aerial imagery plays an important role in various applications such as urban planning, transportation management, and infrastructure maintenance. Road markings serve as vital navigational cues for drivers and are essential for ensuring road safety. Moreover, accurate measurement of road dimensions is necessary for assessing road conditions, planning maintenance activities, and optimizing traffic flow, and also in upcoming technology of self-driving cars.

This report focuses on the exploration and evaluation of methods for detecting road markings and measuring road parameters from aerial imagery. By using computer vision, we aim to develop a robust and reliable system capable of accurately identifying various types of road markings and extracting essential road features from aerial images. Such a system has the potential to enhance the efficiency of transportation management, improve road safety, and contribute to the development of smarter cities.

II. Initial Approach

A. Using Detection based Algorithm

Initially, we considered employing a detection method where the model would be trained by providing bounding boxes. However, acquiring a dataset suitable for this approach posed significant challenges. Upon further examination, we determined that segmentation offers several advantages over detection for road marking detection.

Firstly, segmentation provides finer-grained detail by precisely outlining the boundaries of road markings, resulting in more accurate localization. This level of detail is crucial for tasks such as lane departure warning systems, where precise positioning of markings is essential.

Secondly, segmentation inherently handles overlapping or occluded markings more effectively. Unlike detection, which may struggle with distinguishing individual markings in cluttered scenes, segmentation can segment each marking separately, enhancing overall performance in complex environments.

Furthermore, segmentation enables semantic understanding of road scenes by assigning each pixel a specific class label, facilitating downstream tasks such as road condition assessment or autonomous driving.

As segmentation offers good precision and robustness in handling complex scenarios and enhanced semantic understanding compared to detection methods.Also availability of data makes it a more suitable approach.

III. Dataset

The dataset comprises 1971 high-resolution images depicting roads and traffic scenarios. These images are categorized into three subsets: Train, Valid, and Test.

The training images exhibit a wide range of variations, posing a challenge for model fitting. Additionally, the dataset includes masked versions of the original images, aiding in model accuracy assessment.

Our initial task involves segmenting the original images to isolate road sections, followed by annotating the road markings within these segments. This segmentation and annotation process aims to enhance the model's understanding of road features and improve its performance in accurately identifying and delineating road markings in real-world scenarios.

Fig. 1. Original image

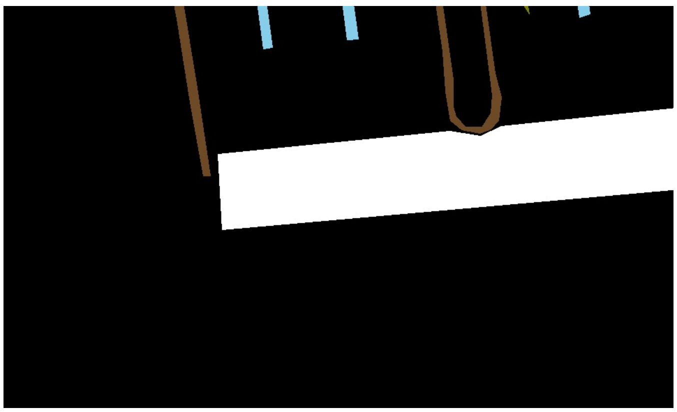

Fig. 2. Segmentation Output

IV. Pseudo Code

A. Algorithm 1 Pre-Processing the Data

```
def PreprocessData(XImages, YGroundTruth):
    data_size = len(XImages)
    XProcessed,YProcessed = [] , []
    for i in range(data_size):
        Resize XImages[i] and YGroundTruth[i]
            to a common size
        Normalize pixel values in XImages[i]
        Append XImages[i] to XProcessed and
            YGroundTruth[i] to YProcessed
    return XProcessed, YProcessed
```

Listing 1. Pre-Processing the Data

```
def TrainUNet(XTrain, YTrain, XVal, YVal,
    epochs):
    UNetModel = DefineUNetModel()
    UNetModel.compile(optimizer='adam', loss='
        binary_crossentropy', metrics=['
        accuracy'])
    for epoch in range(epochs):
        UNetModel.fit(XTrain, YTrain,
            validation_data=(XVal, YVal),
            epochs=10, batch_size=32)
    return UNetModel
```

Listing 2. Training the UNet Model

B. Algorithm 3 Inference on Test Data

```
def Inference(TrainedModel, XTest):
    Predictions = TrainedModel.predict(XTest)
    return Predictions
```

Listing 3. Inference on Test Data

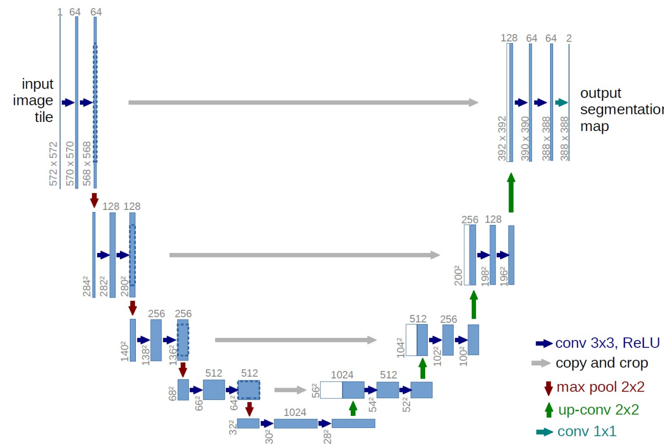

Fig. 3. Skeleton of Process

V. Conclusion

We are in the process of implementing segmentation and mask generation using the UNet architecture for training. As of now, the model training is completed, but we have given the pseudo code that we will be using for the training process.After training, we would be looking for the 'ACapsFPN' architecture which is defined in another paper to be implemented for detecting different type of road markings.

VI. References

[1] Haiyan Guan, Xiangda Lei, Yongtao Yu, Haohao Zhao, Daifeng Peng, José Marcato Junior, Jonathan Li, Road marking extraction in UAV imagery using attentive capsule feature pyramid network, International Journal of Applied Earth Observation and Geoinformation, Volume 107, 2022, 102677, ISSN 1569-8432, https://doi.org/10.1016/j.jag.2022.102677.

[2] S. M. Azimi, P. Fischer, M. Körner and P. Reinartz, "Aerial LaneNet: Lane-Marking Semantic Segmentation in Aerial Imagery Using Wavelet-Enhanced Cost-Sensitive Symmetric Fully Convolutional Neural Networks," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 5, pp. 2920-2938, May 2019, doi: 10.1109/TGRS.2018.2878510.