Large image time series analysis for updating vineyard geographic database

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Objectives :

Introduction

- Segment vineyards from satellite image time series
- Use both **spatial and temporal** information for segmentation
- Correct the "Registre Parcellaire Graphique" (a.k.a R.P.G.)

Constraints :

• There is a lack of annotated data. It is a problem for training and evaluation of deep learning models

Data

R.P.G.:

- represented with polygons
- Updated with farmers declarations : not accurate

- Spatial resolution : 1px = 5m



2D Representations

Why 2D Representations :

- 3D CNNs need a lot of datas
- Generated from a random "segment" -> "data augmentation"

How to build 2D representations :

- Find a serie of pixels by using a random walk algorithm (in the spatial domain)
- Plot the serie of pixels on the horizontal axis and the temporal values of each pixels on the **vertical axis**





CNN Classification & Results Aggregation

CNN Classification :

- Pre-Trained Squeezenet
- Classify 2D representations
- ~90% classification accuracy
- Outputs a "confidence score"

Results aggregation :

- After computing a prediction for each 2D representations
- Compute the **average "vine"** confidence score for every 2D representations passing on the pixel
- Repeat for each pixel
- Leads to a **binary semantic** segmentation result



2D Representations Segmentation

What happens if a segment is generated between vine and "not vine"? Part of the pixels on the segment will be misclassified.

Solution :

- If the **2D representation is** classified as "Vine"
- Segment the different crops in the 2D representation using the average color per columns
- Consider the largest one as "Vine"

Segmentation 2D representation vine crossed by a road Gray : Vine | White : road

Evaluation & Results

Once the results are aggregated, we find the **binarization threshold maximizing** the accuracy on a validation area.

We manually built a ground truth. Then we compare the R.P.G. and our **segmentation** to this ground truth to evaluate it.

Even though our precision is a little below the rpg, we detect more vines and have better global accuracy.

Precision : 0.87 (us) | 0.94 (R.P.G.) **Recall**: **0.89** (us) | **0.54** (R.P.G.) Accuracy : 0.97 (us) | 0.93 (R.P.G.)



White : vines in rpg we detected Red : Vines missing in the RPG we detect Green : Vines we missed

Reference

Chelali, M., Kurtz, C., Puissant, A. & Vincent, N. (2021) Deep-STaR: Classification of image time series based on spatio-temporal representations, Computer Vision and Image Understanding, 208--209:103221