Advanced spectro-bathymetric mapping of shallow seafloor using UAV imagery and deep learning techniques

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ACTYS is a collaborative project between two top FORTH Institutes:

- **Institute of Mediterranean Studies (IMS)**
- **Institute of Computer Science (ICS)**

The goal of the project is to develop an integrated methodology for shallow bathymetry retrieval and detailed mapping of coastal benthic cover of the shoreline.

The ACTYS project ranked 1st in the 2020 FORTH-Synergy proposal evaluation.
Motivation

Advanced speCTro-bathYmetric mapping of Shallow seafloor using UAV imagery and deep learning techniques

Shallow bathymetry is key input to:

- Coastal management/planning projects
- Ecological mapping

Automated seafloor mapping using uncrewed platforms:

- Versatility
- Repeatability

A deep learning approach for:

- Minimizing fieldwork effort
- Maximizing information from input layers
- Landscape-scale mapping of shallow seafloor
Study areas & data acquisition
Study areas & data acquisition

Drone RGB camera

- DJI Phantom4 Pro©
- 20 mPixels
- 1” sensor size
- 120 m survey altitude
- Nadir images

Uncrewed Surface Vehicle (USV) with:
- Sonar sensor / GoPro waterproof camera
  - Sonarmite© BTX single-beam echo-sounder (SBES)
  - Transmitter frequency: 235 kHz
  - Sampling rate: 2 Hz
  - Connectivity: Bluetooth with RTK GPS

Source: Burggraaff et al., 2019
Image pre-processing

Geometric corrections

- Camera calibration with checkerboard
- Camera position from EXIF metadata
- Ground control points with RTK GPS measurements onshore

Radiometric corrections

- RGB Image calibration
  - DN to radiance (dark pixel, vignette, exposure, gain, using Pix4D© software)
  - Radiance to reflectance (with reference reflectance panel in Pix4D© software)

Image resampling for noise reduction

DJI P4P, Green band

Alevizos & Alexakis, 2022
https://doi.org/10.1080/2150704X.2022.2030068
Bathymetry prediction

- Architecture that has been successfully applied in related depth estimation problems (face/hand depth estimation from RGB images).
- Each module consists of Convolutional layers, a bottleneck layer, and Deconvolutional layers.
- A network with 6 stacked hourglass modules.
Bathymetry prediction

The multichannel input of the CNN model consists of several image patches of size $128 \times 128$ pixels that includes five channels input rasters:

- **three channels rasters** for the logarithmic band-ratios (Blue/Green, Blue/Red and Green/Red),
- one for the approximate SfM surface,
- and one with the distance from coast information.
Training Dataset

Concept based on Stumpf et al., (2003) band-ratio model*:

\[
Z = m_1 \ln(nR_w(\lambda_i)) - m_0
\]

* machine learning implementation using multiple ratios

PROS

- Works well for mixed seafloor types
- It is computationally simple and fast

CONS

- Requires input ground-truth depth data
- Requires water-column transparency

Relative depth penetration of light wavelengths in clear coastal waters
Training/testing datasets

**2D sonar measurements (USV)**
- In-situ depth (±10 cm)
- Interpolation for creating train (ground truth) patches for deep network
- Output validation on original soundings

**3D SfM reconstruction (drone)**
- Minimal effect of refraction (very shallow water, nadiral images)
- Use as explanatory variable
- Requires seafloor types with texture (e.g.: rocky reefs)
Training/testing datasets

3D SfM reconstruction (underwater video)
• Sonar data augmentation (MBES of the poor)
• Detailed seafloor texture
• Refraction-free
Experimental Evaluation

Ablation study to show the benefits of the architecture choices and input rasters.
Most related work approaches follow a Single Stack CNN architecture model.

Comparison of our CNN model with conventional Machine Learning approaches.
(Random Forest, Support Vector Machines)

<table>
<thead>
<tr>
<th></th>
<th>Our pipeline, with CNN (full model)</th>
<th>Our pipeline, with RF</th>
<th>Our pipeline, with SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RMSE</strong></td>
<td>0.346m</td>
<td>0.432m</td>
<td>0.599m</td>
</tr>
<tr>
<td><strong>$R^2$</strong></td>
<td>89.4%</td>
<td>84.1%</td>
<td>67.5%</td>
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</tbody>
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<table>
<thead>
<tr>
<th>Single Stack Hourglass model</th>
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</thead>
<tbody>
<tr>
<td><strong>Rasters used</strong></td>
<td><strong>RMSE</strong></td>
<td><strong>$R^2$</strong></td>
<td></td>
</tr>
<tr>
<td>RGB</td>
<td>0.66 m</td>
<td>62.2%</td>
<td></td>
</tr>
<tr>
<td>RGB + SfM</td>
<td>0.62 m</td>
<td>67.7%</td>
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<tr>
<td>RGB + DistCoast</td>
<td>0.51 m</td>
<td>74.6%</td>
<td></td>
</tr>
<tr>
<td>RGB + SfM + DistCoast</td>
<td>0.43 m</td>
<td>85.4%</td>
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<table>
<thead>
<tr>
<th>Full Stack Hourglass model</th>
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<tbody>
<tr>
<td><strong>Rasters used</strong></td>
<td><strong>RMSE</strong></td>
<td><strong>$R^2$</strong></td>
<td></td>
</tr>
<tr>
<td>RGB</td>
<td>0.49 m</td>
<td>79.5%</td>
<td></td>
</tr>
<tr>
<td>RGB + SfM</td>
<td>0.48 m</td>
<td>81.4%</td>
<td></td>
</tr>
<tr>
<td>RGB + DistCoast</td>
<td>0.42 m</td>
<td>83.8%</td>
<td></td>
</tr>
<tr>
<td>RGB + SfM + DistCoast</td>
<td>0.35 m</td>
<td>89.4%</td>
<td></td>
</tr>
</tbody>
</table>

We trained our CNN model on all patches of each study area and then we applied the model on the remaining two areas again for all their image patches.
Results

Area A: RMSE = 0.09m, $R^2 = 0.98$

Area B: RMSE = 0.35m, $R^2 = 0.89$

Area C: RMSE = 0.33m, $R^2 = 0.85$

Area D: RMSE = 0.32m, $R^2 = 0.94$

Training Data = 60%, test data = 40%
Publications

- 4 papers published in peer-reviewed journals
- 3 presentations at International Conferences
- 3 papers are pending for submission to peer-reviewed journals
Conclusions & Future goals

- Accurate depth reconstruction with minimal need for in-situ data - low cost
- Seamless bathymetry prediction over different areas/seafloor types
- Low RMSE values (<0.5m)
- Apply pre-trained model in unknown areas with similar water properties
- Unify entire processing chain into a single software tool
- Require greater amount of ground truth data

Looking forward to future collaborations and extension of the project
Acknowledgements

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• Laboratory of Geophysical – Satellite Remote Sensing and Archaeoenvironment, Institute for Mediterranean Studies
• Computational Vision and Robotics Laboratory, Institute of Computer Science

Thank you very much for attending!