



Soil Roughness Estimation using Digital Images and Artificial Intelligence

Workshop support material

M. Ivanovici, Ş. Popa, K. Marandskiy

The aim of the workshop

- Train students and early-stage researchers on utilization of Artificial Intelligence models for applications in agriculture
- Establish a base for discussion with stakeholders • Farmers, farmer association, private companies, public institutions

The scientific aim

- Al model software and hardware implementation for applications in agriculture
- Target an FPGA or ASIC implementation
 - Real-time performance
 - High-precision running
 - Low power consumption (UAV, satellite)
- Applications in agriculture:
- Soil roughness estimation
- Crop identification etc.

Soil roughness

- Irregularities / variations of the soil profile (or elevation)
- Also called *soil surface roughness*



Factors affecting the soil roughness

- Soil roughness depends on:
 - Farming practices (e.g. tillage)
 - Climatic factors
 - Soil texture
 - Soil properties
 - Formation of soil aggregates presence of clay, iron oxide, organic carbon, calcium carbonate and moisture; also rock fragments and vegetation cover
 - Precipitations
 - leading to a decrease in soil roughness

Importance of soil roughness

- Agriculture is directly conneted to soil
- Soil has to provide adequate physical and chemical conditions for the development of the crop \rightarrow yield
- Soil roughness important physical characteristic
 - Affects various processes at soil level
 - Affects the interpretation of remote sensing data
 - Affects predition of other soil properties
 - Influences short-wave solar radiation

Influence of soil roughness on soil processes

- Determines the water and wind erosion
- Heat exchange
- Development of fauna and flora
- Soil surface temperature
- Moisture and air content in the soil
- Acts as input parameter to various prediction models

Soil roughness estimation methods

- Classical methods (used as references)
 - Roller chain
 - Pinboard
 - Usually both computed on a 1m² area and in several directions
- Original methods
 - Line LASER-based profile complexity assessment
 - Color/gray-scale digital image (top view) complexity assessment*
 - LiDAR-determined profile analysis

*most suited for anisotropic surfaces / materials

Chain method

- Use a 1m-long bicycle chain
- Measure its length on ground surface (profile)
- Compute soil roughness as the chain roughness (Cr) index:

$$Cr = \left(1 - \frac{L2}{L1}\right) \times 100$$

 where L1 = distance over surface (1m); L2 = Euclidian distance measured by ruler

Pinboard method

• Pinboard – variance of pins' height





Our pinboard

- Custom-made pinboard (53 aluminum pins, 33cm long, ½" = 1.25cm gap*)
- *identical to the roller chain;
- Max. 20 cm pin variation (dynamic range)
- Approximate size of the effective measurement line: 72 cm



Pinboard measurements



std = 0.099709302

std = 0.998348 std = 0.921624

LASER-line + digital image acquisition

- Use a red LASER line to emphasize the profile of the soil surface
- Fixed image acquisition conditions (camera position, angles etc.)
- Automatic image analysis (for pin height measurement)



In-lab references and data acquisition



Software golden model

• VGG-11 CNN model implemented using PyTorch • 3 fully-connected layers at the output



Training phase

- The data set:168 grayscale images 200 x 100 pixels
- 66.7% training, 16.6% validation and 16.6% test
- Supervised training of 120 epochs
 - using the Stochastic Gradient Descent (SGD) optimizer with
 - a Mean Square Error (MSE) loss function,
 - a momentum of 0.9 and
 - an initial learning rate of 0.01

• ReduceLROnPlateau learning rate scheduler • with a factor of 0.1 and a patience of 20.

CNN performance

- average pinboard RR prediction error = 5.27%
- accuracy = 94.73%
- the prediction error for each output RR value
- $e = \frac{predicted expected}{expected} \times 100 \, [\%].$

S. Popa, G. Feldioreanu, K. Marandskiy, M. Ivanovici -Convolutional Neural Network Hardware Implementation for Soil Roughness Estimation, 42nd EARSeL Symposium, Bucuresti, Romania, 3-6 July 2023

FPGA-based hardware implementation

- Verilog HDL
- Xilinx Virtex UltraScale+
- weights stored in memories
- 200 MHz clock frequency
- approx. 33 fps
- see more details in:

G. Feldioreanu, S. Popa, M. Ivanovici Convolutional Neural Network implemented on FPGA for trajectory classification ISSCS 2023, Iasi, Romania, 13-14 July



ResNet-18 golden model

- ResNet-18 CNN model implemented using PyTorch
- 1 fully-connected layer at the output



ResNet-18

- average pinboard RR prediction error = 9.29%
- accuracy = 90.71%



Ivanovici, M., S. Popa, K. Marandskiy, and C. Florea. "Deep Automatic Soil Roughness Estimation from Digital Images." European Journal of Remote Sensing, (2024).



Ivanovici, M., S. Popa, K. Marandskiy, and C. Florea. "Deep Automatic Soil Roughness Estimation from Digital Images." European Journal of Remote Sensing, (2024).

Equivalence



set-up with pinboard and laser line (left), laser line-based SR estimation (middle) and pinboard SR measurement (right).

SR = 0.298 in digital images, SD = 0.303 with pinboard, absolute error = $0.005 \rightarrow 1.65\%$

Soil roughness estimation (further reading)

- Fractal complexity assessment of in-situ digital images
 - K. Marandskiy and M. Ivanovici, "Soil Roughness Estimation Using Fractal Analysis on Digital Images of Soil Surface," 2023 International Symposium on Signals, Circuits and Systems (ISSCS), Iasi, Romania, 13-14 July 2023
- Gray-scale, color and multi-spectral (5 bands) images
- Analysis at various altitudes, from drone
 - K. Marandskiy, M. Ivanovici, S. Corcodel and S. Costache, "Multispectral Fractal Image Analysis for Soil Roughness Estimation at Various Altitudes", 13th Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing, Athens, Greece, 31 Oct – 2 Nov 2023

Conclusions and future work

- Soil roughness input parameter for a soil moisture model (elaborated by Tor Vergata) based on Sentinel 1 (SAR) images
- Data augmentation was used (additive noise, rotation, flip, etc.)
- Increasing the size of the training data set to avoid overfitting
- Perform more sistematic in-situ measurements

Open access resources

- Check the project website: <u>https://ai4agri.unitbv.ro</u>
 - Training materials
 - Summer school support material
 - Workshop support material
 - Datasets
- Complete dataset for soil royghness estimation using AI models available on Zenodo – the EU Open Research Repository: https://zenodo.org/records/13141152

Dataset description

Name	Subtree Percentage	Percentage	> Size	Items	Files	Subdirs
Z:\repos\Al4AGRI\soil_roughness_dataset_simple		[0:00 s]	11.7 MB	371	367	4
🖻 📒 resnet18		79.9%	9.4 MB	142	141	1
🗉 📒 all_images		100.0%	9.4 MB	140	140	0
data.csv		0.0%	3.0 KB			
🕀 🚞 vgg11		20.1%	2.4 MB	226	225	1
🗉 🚞 all_images		99.7%	2.4 MB	224	224	0
data.csv		0.3%	6.3 KB			
description.txt		0.0%	2.7 KB			



Further reading

- Ivanovici, M., Popa, S., Marandskiy, K., & Florea, C. (2024). Deep automatic soil roughness estimation from digital images. European Journal of Remote Sensing. DOI: <u>https://doi.org/10.1080/22797254.2024.2342955</u>
- K. Marandskiy and M. Ivanovici, "Soil Roughness Estimation Using Fractal Analysis on Digital Images of Soil Surface," 2023 International Symposium on Signals, Circuits and Systems (ISSCS), Iasi, Romania, 2023, pp. 1–4, DOI: https://doi.org/10.1109/ISSCS58449.2023.10190895
- K. Marandskiy, M. Ivanovici, S. Corcodel and S. Costache, "Multispectral Fractal Image Analysis for Soil Roughness Estimation at Various Altitudes," 2023 13th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS), Athens, Greece, 2023, pp. 1-5, DOI: https://doi.org/10.1109/WHISPERS61460.2023.10431360



The Al4AGRI project received funding from the European Union's Horizon Europe research and innovation programme under the grant agreement no. 101079136.