NEUROEVOLUTION DEEP LEARNING ARCHITECTURE SEARCH FOR ESTIMATION OF RIVER SURFACE ELEVATION FROM PHOTOGRAMMETRIC DIGITAL SURFACE MODELS

ABSTRACT

Development of the new methods of surface water observation is crucial in the perspective of increasingly frequent extreme hydrological events related to global warming and increasing demand for water. Orthophotos and digital surface models (DSMs) obtained using UAV photogrammetry can be used to determine the Water Surface Elevation (WSE) of a river. However, this task is difficult due to disturbances of the water surface on DSMs caused by limitations of photogrammetric algorithms. In this study, machine learning was used to extract a WSE value from disturbed photogrammetric data. A brand new dataset has been prepared specifically for this purpose by hydrology and photogrammetry experts. The new method is an important step toward automating water surface level measurements with high spatial and temporal resolution. Such data can be used to validate and calibrate of hydrological, hydraulic and hydrodynamic models making hydrological forecasts more accurate, in particular predicting extreme and dangerous events such as floods or droughts. For our knowledge this is the first approach in which dataset was created for this purpose and deep learning models were used for this task. Additionally, neuroevolution algorithm was set to explore different architectures to find local optimal models and non-gradient search was performed to fine-tune the model parameters. The achieved results have better accuracy compared to manual methods of determining WSE from photogrammetric DSMs.

Keywords: deep learning · geoscience · neuroevolution · climate change

1 Introduction

Reports from international organizations indicate increasingly significant problems with earths water resources. The global demand for freshwater continues to increase at rate 1% per year since 1980s driven by population growth and socioeconomic changes. Simultaneously, the increase in evaporation caused increasing temperatures leads to a decrease in streamflow volumes in many areas of the world, which already suffer from water scarcity problems. Climate warming is also responsible for globally increased frequency of extreme hydrologic conditions. More intense and frequent precipitation events increase the flood risk as well as heatwaves are becoming more common and last longer, resulting in more severe droughts (UNESCO [2020], IPCC [2015]). Achieving socioeconomic and environmental sustainability under such challenging conditions will require the use of monitoring tools that will facilitate the management of the water resources. Traditional surface water management practices are primarily based on data collected from networks of in situ hydrometric gauges. Point measurements do not provide sufficient spatial resolution to comprehensively characterize river networks, and many developing regions lack them altogether. Moreover, the decline of existing measurement networks is being observed all over the world (Lawford et al. [2013]). Remote sensing methods are
Table 1: Remote sensing small river WSE measurement error comparison. RMSE values taken from: UAV – Bandini et al. [2020], AIRSWOT – Altenau et al. [2017]

| Method                    | RMSE (m) |
|---------------------------|----------|
| UAV RADAR                 | 0.03     |
| AIRSWOT                   | 0.09     |
| UAV SfM DSM centerline    | 0.164    |
| UAV SfM point cloud       | 0.180    |
| UAV LIDAR point cloud     | 0.22     |
| UAV SfM DSM “water-edge”  | 0.450    |

considered as a solution to cover data gaps specific to point measurement networks (McCabe et al. [2017]). A leading example of remote sensing is measurements made from satellites. However, due to too low spatial resolution, satellite data is suitable only for the largest rivers. E.g. SWOT mission allows only observation of rivers of width greater than 50-100 m (Pavelsky et al. [2014]). Small surface streams of the first and second order (according to Strahler’s classification (Strahler [1957])) constitute 70%-80% of the length of all rivers in the world. Small streams play a significant role in hydrologic systems and provide an ecosystem for living organisms (Wohlfahrt [2017]). Despite their high importance, modern methods for their observation are still lacking. In this regard, measurement techniques based on Unmanned Aerial Systems (UASs) are promising in many key aspects, as they are characterized by high spatial and temporal resolution, simple and fast deployment, and the ability to be used in inaccessible locations (Vélez-Nicolás et al. [2021]). Spatially distributed Water Surface Elevation (WSE) measurements are highly important, as they are used for validation and calibration of hydrologic, hydraulic or hydrodynamic models to make hydrological forecasts, including predicting dangerous events such as floods and droughts (Langhammer et al. [2017], Tarpanelli et al. [2013], Jarihani et al. [2013], Domenech et al. [2016], Montesarchio et al. [2014]).

Photogrammetric Structure from Motion (SfM) algorithms are able to generate Orthophotos and Digital Surface Models (DSMs) of terrain based on multiple aerial photographs. Photogrammetric DSMs are precise in determining the elevation of solid surfaces to within a few cm (Ouédraogo et al. [2014], Bühler et al. [2017]). However, they do not correctly represent the water surface. This is related to the fact that general principle of SfM algorithms is based on automatic search for a distinguishable and static terrain points that appear in several images showing these points from different perspectives. The surface of the water lacks such points as it is uniform, transparent and in motion. Due to water transparency, DSMs created using SfM algorithms typically indicate pixel elevations below the actual water surface level. For very clear and shallow streams, photogrammetric DSMs represent the river bottom (Kasvi et al. [2019]). For opaque waters, photogrammetric DSMs are disturbed by artifacts caused by water uniformity (lack of distinguishable photogrammetric key-points). Woodget et al. [2014], Javernick et al. [2014] and Pai et al. [2017] demonstrated that it is possible to read the WSE from photogrammetric DSM at shorelines (“water-edge”) where river is very shallow, so there are no undesirable effects associated with light penetration below the water surface. However, Bandini et al. [2020] proved that this method gives satisfactory results only for unvegetated and smoothly sloping shorelines where the boundary line between water and land is easy to define. For this reason, this method is not suitable for universal automation. Table 1 shows the RMSE errors of existing Remote Sensing methods for small rivers WSE measurements.

The aim of this work was to develop a new automatic method based on deep neural networks allowing estimation of small rivers WSE from photogrammetric DSMs and Orthophotos with an accuracy outperforming previous methods based on manual analysis of photogrammetric data.

2 Dataset

2.1 Dataset structure

In this research, models were trained using brand new dataset, created specifically for the purpose of this work. It consist of 260 samples. Each sample corresponds to a 10 by 10 meter area that encloses river water and nearshore land. Dataset is divided into a training and testing subset at a ratio of 8:2. Dataset is available to download at https://zenodo.org/record/5257183 (Szostak et al. [2021]). Every sample includes the data detailed below.

- **Photogrammetric orthophoto.** True color image represented as a $3 \times 256 \times 256$ array (3 channel image of $256 \times 256$ pixels).
- **Photogrammetric DSM.** Corresponds to the area presented on the orthophoto. Contains disturbed water surfaces elevations. Stored as a $256 \times 256$ array containing elevations of pixels expressed in m MSL.
• **WSE.** Ground truth Water Surface Elevation as single value expressed in m MSL.

![Figure 1: Visualisation of geospatial data from single dataset sample. (a) – photogrammetric orthophoto, (b) – raw photogrammetric DSM with water surface disturbances.](image)

2.2 Dataset preparation

The photogrammetric data and WSE observations needed to create the dataset was obtained during surveys in two study areas:

1. in a ca. 700m stretch of the Kocinka river located near Grodzisko village (Silesian Voivodeship, Poland) on December 19, 2020 and July 13, 2021. This stretch had a WS width of ca. 2m and was overhung by sparse deciduous trees that had no leaves due to the winter season. The banks as well as the riverbed were overgrown with rushes that protruded above the water surface. The banks are steeply sloping at angles of ca. 50° to 90° relative to the water surface. There are marshes nearby, with river water flowing into them in places.

2. in a ca. 700m stretch of the Kocinka river located near Mykanów village (Silesian Voivodeship, Poland) on December 19, 2020 and July 13, 2021. This stretch had a WS width of ca. 3m and was overhung by sparse deciduous trees. Grasses growing on the banks slightly overhang the water surface. The banks are steeply sloping at angles of ca. 50° to 90° relative to the water surface.

In addition, the dataset was supplemented with data from surveys made by Bandini et al. [2019] over a ca. 2.3km stretch of the river Åmose Å (Denmark) on November 21, 2018. See the cited publication for details on this river case study: Bandini et al. [2020].

During survey campaigns, photogrammetric measurement were conducted over the river area. The aerial photos were taken from a DJI S900 UAV using a Sony ILCE a6000 camera with a Voigtlander SUPER WIDE HELIAR VM 15 mm f/4.5 lens. The flight altitude was approximately 77m AGL, resulting in a 20mm terrain pixel. Photos front overlap was 80%, and side overlap was 60%. Alongside the drone measurements, measurements of ground control points were made using RTK GPS receiver. These were used to embed the photogrammetric rasters in the geographic reference system. RTK GPS receivers were also used for reference point measurements of WSE. They were made along the river every approximately 10-20 meters at both banks. Raster files of orthophotos and digital surface models of the investigated areas were generated using Agisoft Metashape photogrammetric software.

The measurement campaigns resulted in raster files with width and height of several tens of thousands of pixels, each representing an area of about 40ha. For use in machine learning algorithms, they were divided into 256px x 256px images representing sub-areas of actual size in the field of 10m x 10m. Point ground truth measurements of river water surface elevation were interpolated using the IDW method. Interpolated values were assigned to individual samples based on geospatial location.

3 Deep Learning solution

3.1 Feature scaling

Input data is subjected to feature scaling before it is fed into the model. DSMs values were standardized according to the equation $DSM' = \frac{DSM - DSM}{\sigma}$, where $DSM'$ – standardized sample DSM 2D array with values centered around 0, $DSM$ – raw sample DSM 2D array with values expressed in m MSL, $DSM$ – mean value of single subjected $DSM$ array, $\sigma$ – standard deviation of DSM array pixel values from the entire dataset. This method of standardization has two clear advantages. Firstly, by subtracting the average value of a single subjected sample, standardized DSMs are always
centered around zero, so the algorithm sees no difference between samples of the rivers located at regions of different altitudes. The actual water level information is recovered during inverse standardization. Secondly, dividing all samples by the same sigma value of entire dataset, ensures that all standardized samples are scaled equally. It was experimentally found that multiplying the denominator by 2 results in better model accuracy, compared to standardization that does not include this factor. Orthophotos were standardized using Imagenet (Deng et al. [2009]) dataset mean and standard deviation according to the equation $ORT' = \frac{ORT - \mu}{\sigma}$, where $ORT'$ - standardized 3-channel ortho photo RGB image 3D array with values centered around 0, $ORT$ - 3-channel ortho photo RGB image 3D array represented with values from the range $[0,1]$, $\mu = [0.485, 0.456, 0.406] - 1D$ vector containing mean values of each of RGB channels from Imagenet dataset, $\sigma = [0.229, 0.224, 0.225] - 1D$ vector containing standard deviation values of each of RGB channels from Imagenet dataset.

### 3.2 Models

The model used to create the supervised learning algorithm for determining a single WSE value is based on the VGG-16 architecture [Simonyan and Zisserman [2015]]. Several variations of this model have been tested:

- **a** VGG-16 **Base Model**. VGG-16 originally used for image classification was modified to perform single floating point value prediction. The changes made to this model are: i) the input size of the model is 4x256x256. It is a four-channel image in which the first channel contains the DSM and the other three channels are RGB orthophoto channels. ii) After a series of convolution layers, a linear transformation of the array data to a single value was applied. No activation function was used on the model output to obtain a floating point value.

- **b** Multiresolution **VGG-16**. VGG-16 Base Model (a) enhanced with multi resolution achieved by concatenation of scaled four-input channels to the output of each max pooling layer.

- **c** **VGG-16 with four conv blocks** - VGG-16 without last three conv layers with changed activation function to PReLU.

- **d** **VGG-16 with three conv blocks** - VGG-16 without last six conv layers with ReLU6.

- **e** **VGG-16 with five blocks** - VGG-16 with whole feature extractor with number of channels 256 changed to 148).

- **f** **fine tuned VGG-16** - best pretrained VGG-16 fine tuned by running neuroevolution with weights mutation.

- **g** **ResNeST50** - Resnet with split attention model

- **h** **VisionTransformer** - Vision Transformer model with different number of heads and depth parameter

- **i** **EfficientNet** - b0 and b1 EfficientNet architectures

### 3.3 Architecture search

Many of recent machine learning works has focused on solutions in which neural network weights are trained through variants of stochastic gradient descent. An alternative approach comes from the field of neuroevolution, which harnesses evolutionary algorithms to optimize neural networks, inspired by the fact that natural brains themselves are the products of an evolutionary process (Faber et al. [2021], Ma et al. [February 2021], Stanley and Miikkulainen [2002], Miikkulainen et al. [Mar 2017], Sun et al. [Oct 2017], E. Galvan [Jun 2020]). In presented work we have set up a neuroevolution based algorithm which can run search through different architectures and modifications of few baseline models VGG, ResNet, ResNEST, EfficientNet, Vision Transformer. The size of population in our experiments was 16 (eq.1 eq. 2). The number of iterations is in range from 20 to 40. The population is set of the models with different initial random weights ((eq.1 eq. 2). Equation 1 describes the definition of the model population where $\theta$ is a weight tensor.

$$P_M = \{F_{\theta i}^l , \Theta = \{\theta_0, \theta_1, ..., \theta_N \} \land i \in \{1,2, ..., population\_size\}\}$$  \hspace{1cm} (1)

$$F_{\theta i}^l (X) = f_{\theta i}^l (f_{\theta i}^{N-1}(f_{\theta i}^{N-2}(...(f_{\theta i}^0))$$  \hspace{1cm} (2)

We define the crossover as a function that has two parent models and an id of the layer as input parameters (Equation (3), alg.1 line 6). It generates two new children models (Equation (4 alg. 2 line 11)).

$$c: Parents \times layer\_id \rightarrow Children$$  \hspace{1cm} (3)

$$c(F_{\theta M i}^l, F_{\theta N i}^l, l\_id) \rightarrow (F_{\theta M' i}^l, F_{\theta N' i}^l)$$  \hspace{1cm} (4)

$$f_{\theta i}^{l\_id} = f_{\theta i}^l$$  \hspace{1cm} (5)
\[
f_{\theta_{l_{id}}}^{i} = f_{\theta_{l_{id}}}^{i}
\]  \hspace{1cm} (6)

The crossover can exchange between parents activation functions, convolutional, or fully connected layers (eq.5, eq.6, alg.2 line 3 and line 6). The last option is to exchange hyperparameters between parents, such as learning rate and weight decay (alg.2 line 9). We define mutation as a function with a model, layer id, and layer features to be mutated as input parameters (Equation 7, alg.3). In this case, the feature and \textit{layer id} determine what the mutation operator will do. It can change the activation function or parameters of convolutional or fully connected layers (depth) (3, line 3 and line 6). The other option is to change the length of the model (adding or removing a layer) or update the hyperparameters. The result is a new modified model (Equation (9)).

\[
m : \text{Parent} \times \text{layer}_{\text{id}} \rightarrow \text{Child}
\]  \hspace{1cm} (7)

\[
m(F_{\Theta_{M}^{i}}, l_{\text{id}}) \rightarrow F_{\Theta_{N}^{i}}
\]  \hspace{1cm} (8)

\[
f_{\theta_{l_{id}}}^{i} = \text{depth}(f_{\theta_{l_{id}}}^{i}) \pm \beta \cdot \Delta_{\text{depth}}
\]  \hspace{1cm} (9)

Finally, evolution process is finished, non-gradient fine tuning is invoked. Fine tuning is performed as weight mutation on a pretrained model (eq.10, eq.11, alg.4). The additional input parameter for the non gradient fine tuning is the scaling factor for computing the value by which the weights can be modified (eq.12). The constant percentage of weights in each weight tensor are selected for fine tuning process. The selection process is done by binary \(\alpha\) tensor. The \(\alpha\) tensor is dynamic and can be different in each fine tuning iteration.

\[
m : \text{Parent} \times \text{scale} \rightarrow \text{Child}
\]  \hspace{1cm} (10)

\[
F_{\Theta_{N}^{i}} = m(F_{\Theta_{M}^{i}}), \Theta' = \{\theta'_{0}, \theta'_{1}, ..., \theta'_{N}\}
\]  \hspace{1cm} (11)

\[
w'_{ij} = w_{ij} \pm \alpha_{ij} \cdot \frac{\text{max}(|\theta_{i}|)}{\text{scale}_{i}}
\]  \hspace{1cm} (12)

\begin{algorithm}
\caption{Neuroevolution approach}
\begin{algorithmic}
\Require \(P_{S}\) - population size, \(M_{B}\) - base model, \(N_{\text{iter}}\) - number of iterations
\State \(P \leftarrow \text{generate population with } P_{S} \text{ size from } M_{B}\)
\For {\text{\textbf{for } } i \text{ in } N_{\text{iter}}}{
\State \text{\textbf{for } } s \text{ in } P \text{ do} \\
\State \text{\textbf{for } } l \text{ do} \\
\State \text{\textbf{end for}} \\
\State \text{\textbf{end for}} \\
\State \text{compute accuracy for all models from } P \\
\State \text{\textbf{end for}} \\
\State \text{take } P_{S} \text{ best models from } P \\
\EndFor
\end{algorithmic}
\end{algorithm}

4 Results and future works

The results are shown in Tab. 2. The models listed in table are those which were set manually (VGG-16 Base Model, Multiresolution VGG-16 Base Model) and other which were generated by neuroevolution search. In parentheses there are combinations of the number of channels for successive blocks inside the models. In the rows where these numbers are not given, the number of channels in the blocks is the same as in the original version of the model. It is shown that neuroevolution search improves accuracy of water level prediction (e.g. ResNeST with modified number of sub-blocks -
Algorithm 2 Crossover operator

Require: \( p_1 \) - parent 1, \( p_2 \) - parent 2, \( l \) - layer for an exchange in crossover

1: \( L \leftarrow \text{get layer} \ l \ \text{from parent} \ p_1 \)
2: \( \text{if} \ L \ \text{is activation} \ \text{type} \ \text{then} \)
3: \( c_1, c_2 \leftarrow \text{exchange activation} \ L \ \text{layer between} \ p_1 \ \text{and} \ p_2 \)
4: \( \text{end if} \)
5: \( \text{if} \ L \ \text{is CONV or FC} \ \text{then} \)
6: \( c_1, c_2 \leftarrow \text{exchange layer} \ L \ \text{between} \ p_1 \ \text{and} \ p_2 \)
7: \( \text{end if} \)
8: \( \text{if} \ L \ \text{is None} \ \text{then} \)
9: \( c_1, c_2 \leftarrow \text{exchange hyperparameters between} \ p_1 \ \text{and} \ p_2 \)
10: \( \text{end if} \)
11: Return \( c_1 \) and \( c_2 \)

Algorithm 3 Mutation operator

Require: \( M \) - model, \( l \) - layer id

1: \( L \leftarrow \text{get} \ l \ \text{layer from model} \ M \)
2: \( \text{if} \ L \ \text{is activation} \ \text{type} \ \text{then} \)
3: \( M' \leftarrow \text{change activation function of} \ L \ \text{in} \ M \)
4: \( \text{end if} \)
5: \( \text{if} \ L \ \text{is CONV or FC} \ \text{then} \)
6: \( M' \leftarrow \text{change parameters of layer} \ L \ \text{in} \ M \) \( // \text{in depth, out depth, filter size, padding etc.} \)
7: \( \text{end if} \)
8: \( \text{if} \ L \ \text{is None} \ \text{then} \)
9: \( M' \leftarrow \text{change optimizer of} \ M \)
10: \( \text{end if} \)
11: Return \( M' \)

Algorithm 4 Fine tuning

Require: \( M_p \) - pretrained model, \( P_S \) - population size of fine tuning, \( N_g \) - Number of generations in the fine tuning, \( p \) - percentage of weights to be perturbated, \( \alpha \) - scaling factor for magnitude perturbation

1: \( P \leftarrow \text{generate population with} \ P_S \ \text{size from} \ M_p \)
2: \( \text{generation} = 0 \)
3: while \( \text{generation} < N_g \) do
4: for \( s \) in \( P \) do
5: \( s' \leftarrow \text{mutate randomly} \ p \ \text{percentage of weights in} \ s \ \text{using} \ [12] \)
6: calculate the fitness of \( s' \)
7: end for
8: \( P \leftarrow \text{choose the} \ P_S \ \text{best solutions and include them in the new population} \)
9: \( \text{generation} \leftarrow \text{generation} + 1 \)
10: end while
11: Return \( P \)

Table 2: Results on 260 images.

| Model                                      | water level estimation error |
|-------------------------------------------|-----------------------------|
| vgg 4 blocks with LeakyReLU (84,137,258,497) | 11.18                       |
| vgg 3 blocks with ReLU                     | 10.44                       |
| vgg 5 blocks with LeakyReLU (66,146,176,222,222) | 10.01                       |
| **fine tuned vgg 5 with LeakyReLU**        | **9.89**                    |
| VGG-16 Base Model                          | 11.69                       |
| Resnet18 Model (42, 193, 293, 579)        | 14.13                       |
| Multiresolution VGG-16                     | 10.50                       |
| **ResneST50 with PReLU (88,192,198,202) [3,5,5,4]** | **8.58**                   |
| EfficientNet-b0                            | 16.12                       |
| EfficientNet-b1                            | 13.75                       |
| **VisionTransformer (depth=8, heads=11)**  | **9.99**                    |
[3,5,5,4], VisionTransformer (depth=8, heads=11)). Our fine tuning approach decrease further the prediction error in VGG model. It is worth to mention that our best deep learning models outperform other manual methods of determining WSE from photogrammetric DSMs and are close to the accuracy of the more complicated and expensive AirSWOT method (Tab. [1]). The future work will concentrate on further model exploration using more sophisticated genetic operators which can modify number of sub-blocks, run models clustering, hyperparameter optimization (Faber et al. [2021]) and automatically apply multiresolution options. Also Bayesian estimation of uncertainty and models sensitivity analysis will be performed (Gal and Ghahramani [2016]).

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