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Validation of Airborne Bathymetry Using Long-Short Term Memory Neural Network

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Abstract. Drones are adaptable technologies that can be used in several applications. They are especially effective in monitoring and surveying tasks due to the low cost and time embedded in such operations. Unmanned Aerial surveys can be repeated with minimal abortive cost and do not require special setup. The ability to carry wide spectrum of airborne sensors render these platforms optimal and compatible with different flight missions and real-time scenarios. This paper carries out a study on bathymetric technique. Datasets obtained by real airborne bathymetry are used to train an LSTM neural network that will be implemented as quality control for the fathometer reading prior to further processing. The extrapolated values will serve as an orienteer for flight mission success depending on auto and partial correlation of the dataset.

Keywords. Quadrotor, bathymetry, flight quality control, LSTM, extrapolation of time series.

1. Introduction

We are living on a planet where 70% of the Earth is covered by water. It is important not only to study how water interacts with other objects on this planet, but also how this volume of water is contained. In other words, it is crucial to understand, record and study these containers life cycles, changes and natural processes. Admitting the broad specter of such science, researchers split the study of water body into many layers. One of these layers is hydrography measures and describes the physical features of the navigable portion of the Earth's surface and adjoining coastal areas.

The bathymetry, a sub element of the hydrography, is a field of science and technology measuring depth of water floors such as oceans, lakes. The recorded charts are useful to support safety of surface or sub-surface navigation and to produce digital terrain modeling in coordination with overground hypsometry technics. The outputs of bathymetric study are important to the following economic fields: navigation safety (example: refer to the recent issue at Suez Canal being blocked by cargo 400-meters ship “Ever Given”, 2021); water volume computation and flood risk analysis; pollution control (example: refer to the environmental catastrophe in the Mexican gulf known as Deepwater Horizon oil spill, 2010); mineral and fish industries; underwater constructions (gas pipelines, fiber-optic telecommunication lines); harbor and dock construction

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activities and shore geotechnical study (example: refer to Gonu Tropical Cyclone hitting Oman coasts, 2007).

2. Bathymetry Methods and Techniques

Bathymetry dates as far as 3000 years ago, where ancient Egyptians frequently used this technique to check the depth of the Nile, study the probability of floods or dryness impacts. The first registered water depth measurement using sounding technique was registered by Posidonius, a Greek geographer, in 85 BC.

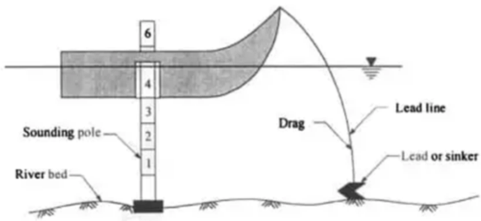

Figure 1. Sounding pole technique

Most of the used techniques, until recently, are characterized as singular point measurement such as the heavy rope or pole dropped from floating ship or the static scaled level measurement (as shown in figure 1). The water depth is measured in Fathom (1.6 m). The sounding pole or rope are called singular point measurement as they study the depth up to which the sinker has reached.

While singular point measurement-based techniques are enough to study well or water tank depth, they are inefficient for coastal water body monitoring, hence, the importance to have multi-points records at the same time.

Submarines and unmanned underwater robots are widely used to perform multiple point bathymetry. Unmanned aerial vehicles are also used to do bathymetry. They come handy in use where submarines are not an option for deployment. For instance, in circumstances where: the water depth is shallow; no point of Entry/Exit; Seaweeds, probability to have mechanical debris and Strong current.

Other techniques are applied for estimating bathymetry and are classified in terms of spatial resolution of measurement and range in water depths shown in figure 2.

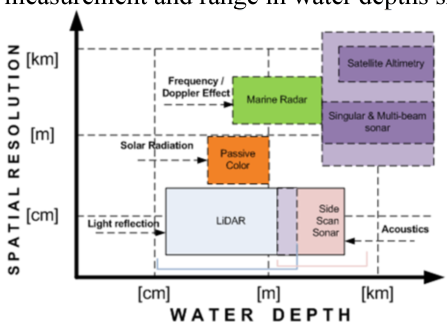

Figure 2. Bathymetry techniques classification

Today, echo sounding is the mostly used. However, at its early implementation, this technique suffered from disadvantages of such method are the lack of details on positioning of the echo-carrier and its embedded time and cost factors. This technique required the following hardware to be performed: an echo-sounder or fathometer emitting waves which are reflected and received back indicating the depth of water. The first echo sounding dates back to 1925, when German ship Meteor sensed mid-Atlantic ridge.

With the advancement in science and technology, improved echo-sounder were used to measure water depth such as the Precision Depth Recorder (PDR) encompassing a high frequency sound beam emitter. Nowadays, Echo sounders used multi-beam frequencies and side scan sonar and acoustic instruments such as Geological Long-range Inclined Acoustical Instrument (GLORIA) or SEA-MARK standing for Sea Mapping and Remote Characterization. These instrumented are usually towed to a ship and provide detailed measurement. The disadvantages of such method are the time and cost embedded for logistics and mobilization of the setup and overlapping over the site. The method cannot be used for shallow water due to the weight of the ship.

With the development of drones' application, the recent airborne hardware reliability, aerial bathymetry is considered to have several advantages over the aforementioned techniques. It is especially considered to have quick setup and deployment, enhanced maneuverability with reference to manned and unmanned boats. Overlapping and repeatability of measurement is of minimal costs. In addition, airborne laser scanning technology are can be used to simultaneously survey both land and coastal waters in a single approach. This is done by deploying a technique known as Airborne LIDAR Bathymetry (ALB) or Airborne LIDAR Hydrography (ALH) which uses state-of-the-art LIDAR Technology to measure sea bed depths and topographic features rapidly and accurately.

3. Case Study

Bathymetric uncertainties or deviation of the readings are facts to be dealt with during data processing. Data acquisition is extremely vulnerable node in airborne bathymetry: for instance, some of the frequent causes for bad results are: the zero-positioning of the LiDAR or Echo-sounder has not been taken into consideration during parametrization step, the sensitivity of the sensor [1], the multi-beam echo sounder itself and RTK receiver setup [2]. Error impacts are categorized in polynomial orders and severity. Doppler effect for both - frequency modulated signals (FM) and - continuous wave (CW) are affects nearly by 82% on rough stat and 68% on calm state of the total uncertainty. As for the baseline decorrelation, it depends on the actual pulse shape chosen. Vertical uncertainties induced by the source are predicted to be larger for FM than that of CW. This is confirmed by a comparison between the modelled and measured effect on depth uncertainties when switching to FM [3]. The uncertainty is divided into second-order (imperfectness of the Doppler-range correction) and first-order (effect on beam-steering) effects. Water transportation traffic and sea states (calm/rough) should also be considered. This will have impact on the global trajectory planning of the drone: global path planning is the chosen path prior to flight (straight, clusters, overlapping and zig-zag path), velocity and altitude of the flight especially that the airborne sensor affects the position of center of gravity of the drone, which should be considered during control design [4].

Taking the aforementioned into consideration, it is clearly noticed the importance of having quality control algorithm on each milestone of the bathymetric measurement in order to avoid excessive abortive works. After the trajectory planning and flight mission is set, it is important to microscopically and macroscopically to analyze the datasets: the correlation of the numbers and whether a particular case affects its future value or not. This can be done mathematically using auto and partial correlation. We propose using Long-short term memory neural network that will act as quality controller. Obtained data set as filtered and part of them are fed into the controller for training and then extrapolating future values. The latter will be used as an orienteer for the mission success. This recommendation system will assist the operator to validate or cancel the mission at an early stage avoiding cumulative time and cost implications.

For this paper we will use datasets taken from real bathymetric measurement in Denmark[2]. The equipment and software used during this mission: during the process are the following: Echo-logger ECT400S echo sounder, UgCS SkyHub/true terrain following system with a radar altimeter, UgCS onboard software for echosounder data logging, UgCS ground control software, DJI M210 V2 RTK drone, Hydromagic processing software. Datasets encompasses data in NMEA 0183 format, recorded by SkyHub, data of manual depth profiling in October of 2020. Coordinates are in UTM 32N, vertical datum DVR90 and a report based on manual depth profiling. It should be noted that the drone lost RTK lock during the survey, it was not possible to use altitude recorded by GPS on the drone for elevation calculation. Nevertheless, the dataset will be used and adopted as it was provided to put more difficulties on LSTM and to avoid overlearning from identical training datasets.

4. Extrapolation of Echo-Sounds Data Using LSTM

Long short-term memory or LSTM was optimized as a solution for the vanishing gradient problem [5] that can occur during weight training of a recurrent neural network. LSTMs are used extensively in the machine learning problems and are applied for handwriting recognition [6], speech recognition [7], machine translation [8] and time series forecasting [9-12]. LSTM has two recurrent features: the hidden state or h and the cell state c. The LSTM cell is represented mathematically using equation [1]:

$$\left(h^{(t)}, c^{(t)}\right) = \mathcal{L}(h^{(t-1)}, c^{(t-1)}, x^{(t)}) \tag{1}$$

Where the inputs to the cell $\mathcal{L} - h^{(t)}, c^{(t)}, h^{(t-1)}, c^{(t-1)} \in \pm\mathbb{U}$ and $x^{(t)} \in \mathbb{R}^d$ and $h^{(t)}, c^{(t)} -$ are the two generated outputs which are fed to the cell at time $t+1$. At any time of point of time t, an element of the input sequence $x^{(t)} \in \mathbb{R}^d$ is also fed into the cell $\mathcal{L}$. Inside the cell $\mathcal{L}$, the hidden state h and the input vector are fed into three gates [10], each of which produces a scalar value in $\mathbb{U}$ with the help of a sigmoid activation function:

$$\begin{aligned} f\_g^{(t)}(x^{(t)}, h^{(t-1)}) &= \sigma(W_{f,x}^T x^{(t)} + \omega_{f,h} h^{(t-1)} + b_f) \in \mathbb{U} \\ i\_g^{(t)}(x^{(t)}, h^{(t-1)}) &= \sigma\left(W_{i,x}^T x^{(t)} + \omega_{i,h} h^{(t-1)} + b_i\right) \in \mathbb{U} \\ o\_g^{(t)}(x^{(t)}, h^{(t-1)}) &= \sigma(W_{o,x}^T x^{(t)} + \omega_{o,h} h^{(t-1)} + b_o) \in \mathbb{U} \end{aligned} \tag{2}$$

Where $W_{f,h}, W_{i,h}\ and\ W_{o,h} \in$ and $\omega_{f,h}, \omega_{i,h}, \omega_{o,h}, b_f, b_i$ and $b_o \in \mathbb{R}$ are the weight vectors and the bias respectively. They consist the parameters that the neural network

[2] Data provided by Geopartner Landinspektorer A/S (https://geopartner.dk/)

will have to optimize in order to keep the mean squared error minimal hence extrapolating with minimal deviation. The forget gate $f\_g^{(t)}$, the input gate $i\_g^{(t)}$ and the output gate $o\_g^{(t)}$ – function as a switch relay when their output values approach the value of zero or one. The forget gate set the parameters of when the current state $c^{(t)}$ should be whipped and updated by the input gate, that set the frequency of updates of the cell state, the output gate controls how much of the cell state should exit the cycle and become the new hidden state. The cell update is represented by a scalar (c_u), which by itself is a neuron with hyperbolic tangent activation function and can be represented using the following equation:

$$c\_u^{(t)}(x^{(t)}, h^{(t-1)}) = \tanh\,(W_x^T x^{(t)} + \omega_h h^{(t-1)} + b) \in \pm\mathbb{U} \tag{3}$$

Where $W_x \in \mathbb{R}^d$; ω_h and $b \in \mathbb{R}$ – are further weight parameters to be learned. Once the cycle is order for update the new hidden and cell states are calculate using the following equation:

$$c^{(t)} = f\_g^{(t)}.\,c^{(t-1)} + i\_g^{(t)}.\,c\_u^{(t)} \in \pm\mathbb{U} \tag{4}$$
$$h^{(t)} = o\_g^{(t)}.\tanh\,(c^{(t)})c^{(t)}$$

The program structure on of LSTM in python is divided into 8 steps: firstly, the libraries dependencies are imported. The results are obtained using $Tensorflow$ and $keras$ libraries. Second step is to identify the index and features are per paragraph 3. The 3rd step is to use the combined multi-features to train LSTM and obtain the best weights and bias as per equation [2]. The 4th step is to compile the model as per equations [5;8]. The 5th step is to fit the model and data flattened in the 6th step. Next in the 7th step, the fitted model is validated using validation data and tested in the 8th step that generates the extrapolation results. We will start by checking the autocorrelation between the given recorded time series and a lagged version of the same data. Mathematically autocorrelation is calculated used the following equation:

$$\widehat{\rho_x} = \frac{\sum_{t=k+1}^{T}(r_t - \bar{r})(r_{t-k} - \bar{r})}{\sum_{t=1}^{T}(r_{t-k} - \bar{r})^2} \tag{5}$$

Where, r_t – is the time series sorted in ascending order; r_{t-k} –is shifted or lagged time series by k-units; $\bar{r}$ – is the average of the time series. The result of the autocorrelation is show in figure 3.

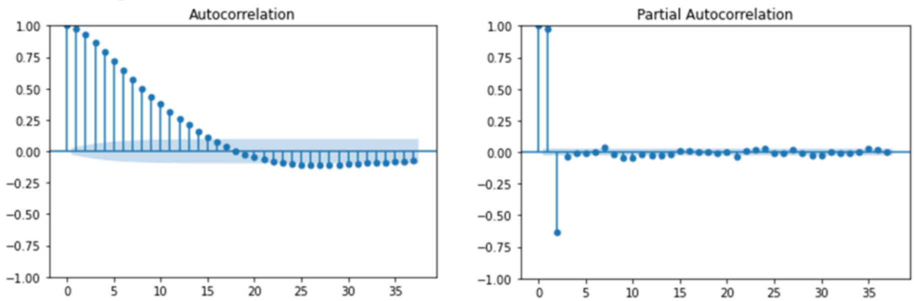

Figure 3. Auto and partial correlation between initial and lagged time-series

Usually, the values of autocorrelations are between -1 and 1; where the negative and positive signs indicate the level of influence of certain parameter on its future value. For more validation, partial correlation is also computed. This is used for special cases when we want to observation in a given time with the observations own lagged value, unlike autocorrelation, where we find the relationship between a time series point to the whole past time series. Next, after the model is fitted, trained and validated, prediction results can be obtained as per the computation equations [1,4]. The results of the extrapolation data are shown in figure 4.

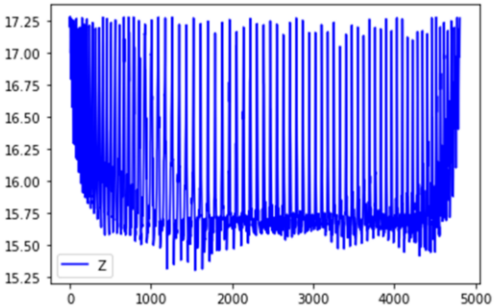

Figure 4. Extrapolation results of water depth using LSTM

5. Results and Discussions

Extrapolation data shows that the water depth of the lake is between [15,25 ;17,25] meters. The statistical deviation of the readings from the real values is 5,59 and it refers to the root mean square error. A graphical illustration comparing the real values to the extrapolated values is depicted in figure 5.

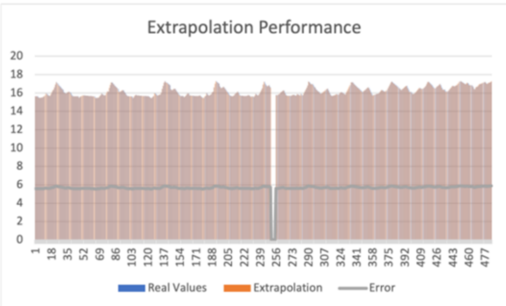

Figure 5. Performance of LSTM

The same can be verified by crosschecking with the bathymetry readings and data processing vide Hydromagic software.

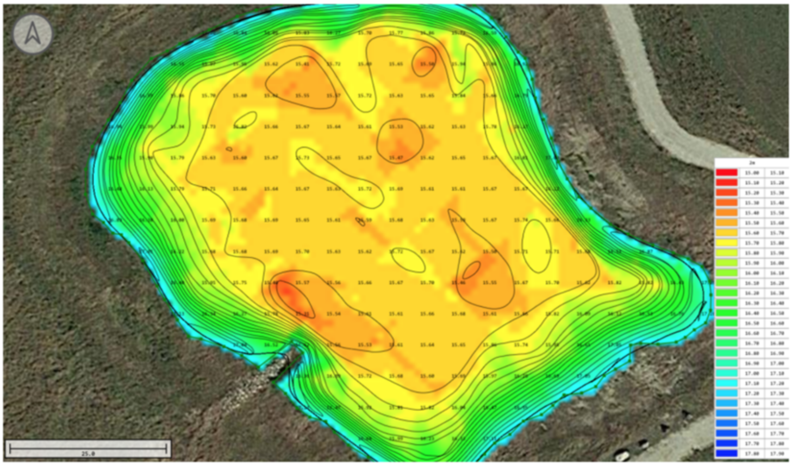

Figure 6. Fathometer readings

In figure 6, it is clear that the edges of the lake show of 17 meters on average the same is confirmed in figure 5, where the edges are of 17.25 meters and the shallowest depth is around 15 meters. As such it can be practically confirmed that LSTM can be used as a quality controller for the bathymetric measurement, depending on the auto and partial correlation of the data sets with their future values. The extrapolated data can be also used to check seasonal deviation of the water level.

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