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Processing of Heading Data with Machine Learning for MBES Survey

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ABSTRACT: The paper presents research on using machine learning algorithms for heading signal smoothing recorded during MBES surveys. Several numerical methods, typically used for time series smoothing and prediction in Data Science applications are tested, like moving average, Gauss filter, Holt Winters filter and Wittaker filter. Additionally, recurrent neural networks are analyzed. Data from real use cases are used and parameters of the methods are verified. The methods are validated against smoothing performance (with variance analysis) and against original function fitting (with RMSE), allowing the qualitative and quantitative assessment. Open source python libraries are used. The results shows efficiency of such approach for this problem.

1 INTRODUCTION

Multibeam Echosounder is nowadays state of the art for hydrographic surveys, due to the accuracy and coverage that it offers. Complete MBES system however requires a set of additional sensors allowing precise navigation and measurements, like positioning sensor, motion reference unit or speed sensor. Data obtained form these sensors influence a lot accuracy of measured data and consequently of bottom model obtained. Raw measurements from these sensors are burden with typical measurement errors and inaccuracies, therefore these data requires filtration in processing stage to provide reliable values for the MBES system. Heading is one of the crucial information responsible for the direction of beams in echosounder, allowing proper alignment of the system in the survey area. Heading is obtained from gyrocompasses, but more and more often it is based on GNSS measurements in satellite compasses. Measurements form both systems may be burden with inaccuracies and errors however satellite compasses may additionally be affected by signal propagation issues (e.g under the bridge or in dense urban environment). Therefore filtration of raw data is needed. The goal of it is basically to filter the data by deleting outlier, removing peaks and generally to smooth signal distribution over time.

In recent years, machine learning (ML) methods have emerged as powerful tool capable of modelling complex relationships in large datasets. Their ability to learn patterns from data makes them particularly attractive for tasks involving signal denoising and smoothing, where classical model-driven approaches often face limitations. Techniques such as Support Vector Regression (SVR), deep learning-based models and recurrent networks (LSTM, GRU, RNN) have shown promising results in various time series and signal processing applications, including inertial navigation, GPS trajectory smoothing, and sensor fusion.

The aim of the research for this paper was to analyze and compare several machine learning methods and their key parameters in the context of heading data filtering for MBES surveys. This study aims to assess their effectiveness in reducing noise while preserving the actual dynamics of vessel motion. Real-world heading measurements, collected during hydrographic surveys, will be used for this analysis. The bathymetric data were collected using an echo sounder PING DSP 3DSS-DX-450 mounted on the survey vessel Hydrodron-1. The data were gathered during the project LIDER/4/0026/L-12/20/NCBR/2021. Unlike synthetic datasets, real survey data capture the full spectrum of operational challenges, such as environmental disturbances, sensor imperfections, and vessel maneuvers, thus providing a robust benchmark for evaluating ML-based filtering approaches. The processing methods were elaborated in the scope of the project SONARMUS supported by the Foundation for Polish Science (FNP) in the FENG Proof of Concept program under grant no. FENG.02.07-IP.05-0489/23

2 LITERATURE REVIEW

Accurate heading data are crucial for the quality of bathymetric surveys conducted with MBES systems. Traditional filtering approaches such as moving average filters, low-pass filters, and Kalman filters have been widely used in hydrography to mitigate these effects. Kalman filtering has been popular due to its optimality under certain assumptions of Gaussian noise and linear dynamics. Vessel motion can be highly non-linear, especially during turns, speed changes, or under the influence of waves and currents. Consequently, interest has grown in using data-driven machine learning (ML) approaches to capture such complex behaviors. For example Support Vector Regression (SVR) has been applied successfully in GPS data denoising [1]. Deep learning methods, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models, have shown capabilities in modeling time-dependent patterns in many fields related to geodata. A fine survey on this is given in [2].Despite their successes in related fields, ML methods have not yet been widely adopted in MBES data processing workflows. Recent studies suggest that they may offer significant advantages, especially in cases where traditional models fail to effectively filter heading data without introducing delays or signal distortions [3]. Given the growing interest in applying machine learning methods in hydroacoustic, the following section presents a literature review on their use in processing data from MBES systems.

2.1 *Machine Learning in MBES Data Processing*

Machine learning (ML) has been a growing tool in multibeam echosounder (MBES) data processing in recent years. ML techniques have been widely explored to improve feature detection, classification, noise reduction, and point cloud denoising.

Ling et al. used neural networks to denoise point cloud data from MBES systems. Their approach, based on score-based generative models and 3D point cloud processing techniques, effectively detects and removes noise in MBES data. [4]

For feature detection, Snijder and Lekkerkerk introduced the Multibeam Object Detection Inferencer (MODI), a convolutional neural network (CNN) specifically trained to identify seabed features such as shipwrecks and geological formations automatically. This work demonstrates the increasing feasibility of deep learning for autonomous interpretation of MBES datasets [5].

Beyond object detection and denoising, semi-supervised ML methods have gained traction for water column target detection [6] and for matching MBES data with side scan sonar [7].

ML-based approaches have also been used in post-processing step, which significantly improved accuracy and repeatability in identifying noise and artifacts [8], for example with Convolution Neural Networks [9, 10]. A complementary review by Gauchia et al. emphasized the need for hybrid automatic and semi-automatic data cleaning strategies in hydrographic workflows [11].

Interesting approaches for seafloor classification and spectral analysis can be found in zones [12] or [13].

2.2 *Heading estimation and navigation integration*

Heading data plays a central role in ensuring precise georeferencing of MBES measurements. Traditional model-based approaches, such as Kalman filtering, are widely used, but recent ML advancements offer promising alternatives for improved heading estimation.

Dahan and Klein introduced GHNet, a deep learning framework capable of regressing heading angles using GNSS-derived velocity data, even at low speeds. This approach surpassed conventional methods in accuracy and robustness [14]. Furthermore, Engelsman and Klein explored learning-based gyrocompassing to estimate heading from low-performance gyroscopes without needing long-term integration or model-based corrections [15].

In the context of autonomous ship navigation, Wright examined the integration of multi-sensor inputs—including heading, speed, and orientation—using deep learning for dynamic vessel control. These techniques are increasingly crucial in hydrographic operations involving unmanned surface vessels (USVs) [16].

TransNav has also featured studies on machine learning-driven navigation systems, such as using NeuroEvolution of Augmenting Topologies (NEAT) for ship handling optimization [17] and ML-based methods for maritime risk assessment [18]. Both studies emphasize the importance of accurate heading data as a critical input for safe and efficient vessel operations.

Heading data estimation, being a part of pre-processing stage, have been also analyzed in wider context of acoustic data curation. Thompson, Li, and Garcia (2023) assessed various preprocessing strategies for echosounder data used in ML applications. Their study emphasized that consistent normalization and segmentation protocols have a direct impact on model performance and generalization capabilities [19]. Similarly, Thompson et al. (2022) conducted an evaluation focused on fisheries acoustics and found that the choice of preprocessing strategy can substantially affect the interpretability and effectiveness of ML models [20]. Interestingly, Ling et al. in [21] presented a benchmarking study using both classical and deep learning methods, demonstrating that while machine learning (ML)-based approaches are promising, traditional methods like Generalized Iterative Closest Point (GICP) still provide superior accuracy in fine alignment stages.

The above review shows that, some work have been already done and using of ML for MBES is becoming a hot topic. However despite significant advances, several gaps remain in the application of ML to MBES data and heading processing, showing future directions, like non-linear noise sources, real-time heading estimation or integration with existing systems and software. Addressing these gaps can accelerate the adoption of ML in MBES workflows and improve both the efficiency and accuracy of hydrographic surveys.

Therefore in these paper we are showing research on utilization of ML and numerical methods for heading data processing with the use of typical open libraries used in data science to prove their usability in assumed scenarios.

3 FILTRATION METHODS

The filtration, understood as removing outliers and smoothing of navigational data (e.g. heading), can be made with the use of methods traditionally used in data science. For the needs of this paper we can divide them into two categories – numerical methods and machine learning methods. In this paragraph we provide a very brief description of the methods used in our research, which in fact is only a part of available options.

3.1 *Numerical filtration*

Heading filtration during MBES survey can be understood as time series filtration. This approach may include a large variety of available filters, used for time-series data science. In many cases they are used to predict future values and to find trends (e.g. stock exchange or weather prediction). In our case the processing is rather focus on outliers and smoothing. Various methods can provide various advantages. Low pass filters (moving average, Gaussian) quickly damp high frequency noise, while model based smoothers (ARIMA, Holt Winters, Whittaker) adaptively track the underlying data with adjustable stiffness. In our research numerical filters are used as a benchmark for comparing with ML approach. In this case we used moving average and Gauss filters as examples of low-pass filters and Holt-Winters and Whittaker filters as examples of model-based smoothers.

A moving-average (MA) filter replaces each sample by the arithmetic mean over a symmetric window of width 2k+1, as in equation (1).

$$y_t = \frac{1}{2k+1}\sum_{i=-k}^{k} x_{t+i} \tag{1}$$

It is in fact a simple finite-impulse-response (FIR) low-pass, giving strong attenuation of high-frequency jitter (e.g., wave-induced yaw) with low computational cost and simple interpretation [22]. Main drawback is however a fixed k-sample group delay in causal operation and edge effects near the start/end of a line.

Another FIR approach is a Gaussian filter in which a Gaussian window is provided to replace the rectangular kernel, as given in eq. 2, where sigma is a smoothing parameter, allowing to adjust filter's sensitivity. Thus Gaussian filter minimises ringing for a given effective width and reduces frequency sidelobes relative to the MA [22].

$$y_t = \frac{\sum_{i=-m}^{m} g_i\, x_{t+i}}{\sum_{i=-m}^{m} g_i},\ g_i = exp\left(\frac{-i^2}{2\sigma^2}\right) \tag{2}$$

Gaussian filter is preferred when preserving the curvature of gentle turns and smoothing factor allows to fit to actual curvature.

In contrast to these fixed-kernel convolutions, Holt–Winters exponential smoothing formulates the signal as latent level (and optionally slope/seasonal) states updated by exponentially weighted averages, e.g., additive trend, playing the role of the smoothed output [23]. However, the effective cutoff is signal-dependent: during sharp course alterations the filter lags, unless parameters are adapted or robust variants (e.g., bounded-influence update rules) are employed.

The idea of Whittaker (Eilers–Whittaker) smoother is to cast smoothing as penalised least squares, based on is the discrete second difference operator. As a result a cubic spline like smoother with explicit control of stiffness through single parameter is achieved. It is computationally light for dense heading logs but sensitive to the choice of smoothing parameter.

In practice, MA/Gaussian filters serve as fast baselines and as pre-conditioners for learning pipelines; Holt–Winters provides an online, interpretable tracker for low-order dynamics and Whittaker offers a principled post-processing smoother with tuneable rigidity. In our case they serve as comparing benchmark to ML filters.

3.2 *Machine Learning filtration*

Recurrent Neural Networks and their variations are the ones among many other Machine Learning methods, most commonly used for smoothing tasks. They can act as adaptive, non-linear smoothers also for vessel heading in MBES surveys. Their usage is for this purpose means to train them to minimize a reconstruction or one-step-ahead prediction loss; in deployment they operate causally for real-time use or bidirectionally (zero-phase) for post-processing.

A traditional, simple RNN updates a hidden state with a non-linear recursion and emits a linear readout as the smoothed estimate (eq. 3, 4). It behaves like a data-driven IIR low-pass: steady segments yield strong attenuation, while turns increase effective bandwidth.

$$h_t = \varphi\left(W_{xh}\, x_t + W_{hh}\, h_{t-1} + b_h\right) \tag{3}$$

$$\hat{y}_t = W_{hy}\, h_t + b_y \tag{4}$$

where: h_t — hidden state vector at time t; φ — element-wise nonlinearity (tanh/ReLU); W_{xh} — input→hidden weights; x_t — input at time t (e.g., heading and auxiliaries); W_{hh} — recurrent weights; h_{t-1} — previous hidden state; b_h — hidden bias. $\hat{y}_t$— smoothed or predicted heading at time t; W_{hy} – hidde to output weights; h_t — current hidden state; b_y— output bias.

The advantages includes minimal parameter count and memory requirements, while the main limitation is vanishing/exploding gradients, which restrict temporal memory.

LSTM and GRU are widely known modifications of RNN, coping with vanishing gradients. The Long Short-Term Memory augments the RNN with gating and a persistent cell state, mitigating gradient pathologies and extending effective memory. In practice, small causal LSTMs (1–2 layers, 16–64 units) run in real time on survey hardware. Regularization (dropout, weight decay) is recommended to avoid overfitting short calibration runs. The Gated Recurrent Unit simplifies the LSTM by merging input/forget behavior into an update gate and using a reset gate. It offers comparable accuracy with fewer parameters and faster convergence, which is attractive under tight CPU budgets on board. For very long or highly non-stationary legs, LSTMs may hold a slight edge due to the explicit memory cell [24, 25].

Based on the popularity for time series tasks, these networks were selected for the research in this paper.

4 RESEARCH METHODOLOGY

This chapter provides description of the methodology used in research for this paper. It is based on real data and post-processing experimental analysis with various filters.

The goal of the research was to analyse the performance of ML approach for heading filtration during MBES measurements. Typical ML filters used for time series analysis were used and popular numerical approaches as benchmark. The data for experiment was acquired with real devices and the analysis was made in post-processing stage with own scripts and algorithms.

4.1 *Data acquisition and processing*

Data for the research were acquired during hydrographical surveys performed with the Autonomous Surface Vehicle HYDRODRON by Marine Technology Ltd. [26]. Hydrographic data were acquired with PING 3DSS-DX-450 sonar and heading data with SBG Ekinox2 Subsea, which is an advanced inertial navigation system providing position, heading, speed and inertial information. The ASV used for the research is presented in figure 1.

Figure 1. ASV HYDRODRON-1 by Marine Technology Ltd. used for the data acquisition

Data were acquired in two areas. The first one was at the Pomorskie quay in Presidential Basin in Port of Gdynia, while the other one was located in Zawory in Kłodno Lake. Both surveys included full MBES with INS recordings. Data were collected with HYPACK software pack in raw txt format. The first area is a harbour area with maintained depth, yet as the area are not wide, the surveys requires many profiles and manoeuvres between them. These may influence the stability of the heading measurements. The other are is a natural lake and the survey required following profile patterns. In this paper the first area is included, after initial analysis, as it covers more turns and heading fluctuations.

Acquired data included 6 files for the first area with complete recordings from sensors gathered by Hypack. The data was provided in txt files, which were then processed via scripts in Python language. The scripts were launched in notebooks within Google Colab platform, which is a hosted Jupyter Notebook service that requires no setup to use and provides free access to computing resources, including GPUs and TPUs.

Entire processing, including visualization with graphs in this paper and statistical analysis was performed within this platform. Following open-source libraries were used for data processing and visualization: pandas, matplotlib, numpy, statsmodels, scipy, whittaker_eilers, sklearn and tensorflow.

4.2 *Evaluation Metrics*

The goal of filtering heading data, as well as for other auxiliary sensors is to provide a reliable, accurate, yet sufficiently smoothed signal. Therefore for performance assessment of the filters we were analysing both – the roughness of the produced trajectory and the accuracy, understood as the distance to the unfiltered data. Generally the task is to minimize the roughness of the function, while simultaneously maximizing the accuracy.

For roughness measurements we use three metrics:

– Standard deviation
– Sum of squared second differences (SSSD)
– Variance of local first differences

Standard deviation of first differences (global) – eq. (5) is a compact, window free indicator of overall roughness.

$$\sigma_{\Delta y} = \sqrt{\frac{1}{(N-1)} \Sigma_{t=2}^{N} \left(\Delta y_t - \mu_{\Delta y}\right)^2} \tag{5}$$

where: $\sigma_{\Delta y}$ — sample standard deviation, $\mu_{\Delta y}$ — global mean; N — sample count

Sum of squared second differences (SSSD) aggregates discrete curvature and highlights residual oscillations (eq. 6).

$$SSSD = \Sigma_{t=3}^{N} \left(y_t - 2y_{t-1} + y_{t-2}\right)^2 \tag{6}$$

where: y_t — heading at discrete time t; N — sample count

Variance of local first differences (eq. 7) on the other hand is a windowed statistic, which diagnoses short scale jitter around a given time index.

$$Var_w(\Delta y)_t = \frac{1}{|W_t|-1} \sum_{i \in W_t} \left(\Delta y_i - \overline{\Delta y}_{Wt}\right)^2$$
$$\Delta y_i = y_i - y_{i-1}, \quad \overline{\Delta y}_{Wt} = \frac{1}{|W_t|} \sum_{i \in W_t} \Delta y_i \tag{7}$$

where: W_t— centred index window around t with size $|W_t|=w$; $\mu_{Wt}(\Delta y)$— mean of first differences within this window.

For assessing the accuracy, we use typical indicating values:
– Mean Absolute Error (MAE);
– Root Mean Square Error (RMSE).

Mean Absolute Error (MAE) is a scale-preserving measure robust to occasional outliers, according to eq. 8:

$$MAE = \frac{1}{N} \Sigma_{t=1}^{N} \left|y_t - \hat{y}_t\right| \tag{8}$$

where: N — number of paired samples; y_t— reference (ground truth) heading at time t; $\hat{y}_t$ — model estimate at time t. In our case real measured value is set as ground true |·|.

While MAE is less sensitive to large residuals, Root Mean Square Error (RMSE) emphasises large deviations by squaring residuals before averaging and taking a square root (eq. 9):

$$RMSE = \sqrt{\frac{1}{N} \Sigma_{t=1}^{N} \left(y_t - \hat{y}_t\right)^2} \tag{9}.$$

This set of measurements indicators allows to assess the quality of the filtration in terms of roughness and accuracy.

5 RESULTS

The results are presented in two parts. Firstly we provide results achieved with numerical methods for the area near Pomorskie quay. Then the same data are analyzed with neural methods. Such approach led to comprehensive analysis of the results.

5.1 *Pomorskie quay area – numerical methods*

In this area, data were acquired from six survey profiles. Gyro heading along time, for an example profile is presented in figure 2. Generally the course was stable, however some rapid fluctuations in some places arose. These can affect final data and should be filtered.

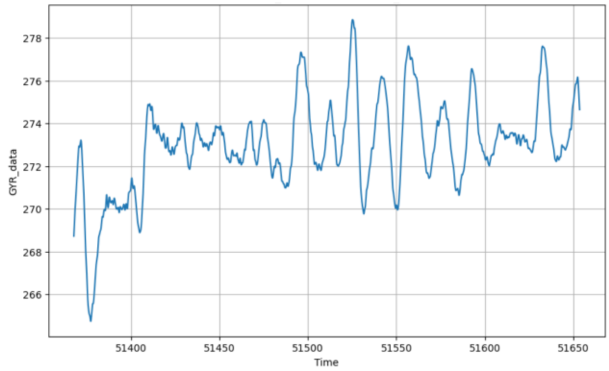

Figure 2. Raw gyro heading for one of analysed profiles.

In figure 3 selection from this profile is presented, showing the efficiency of filtration of numerical methods.

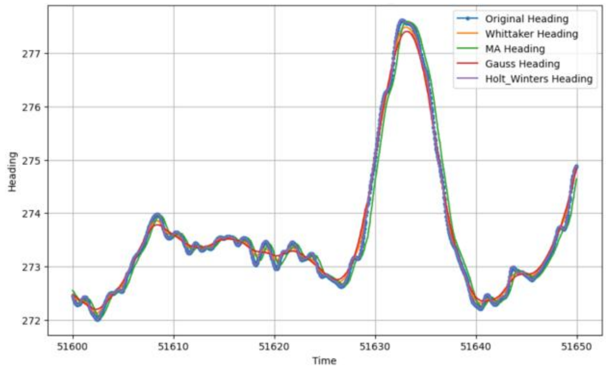

Figure 3. Numerical filtration for gyro heading – selected part of the profile.

The metrics for this profile, showing roughness and smoothness are given in table 1. The analysis of the table confirms that proposed metrics can be used for roughness and smoothness assessment. However standard deviation seems to be less sensitive than SSSD. In the presented example, the most smoothed values were achieved with Gaussian filter, which resulted in small SSSD and other smoothness metrics. Simultaneously MEA and RMSE were higher than Holt-Winters, yet still smaller than Moving average. Based on this example Whittaker filter showed the best balance between smoothness and roughness. This can be also observed on the graph in figure 3.

Table 1. Metrics for numerical filters for example profile.

Method	Standard deviation	SSSD	Variance of local diff.	MAE	RMSE
Raw data	2,17	2,34	0,00109	0	0
Whittaker filter	2,12	0,004	0,00069	0,076	0,098
Moving average	2,16	0,021	0,00085	0,211	0,28
Gauss filter	2,10	0,002	0,00062	0,118	0,15
Holt-Winters filter	2,17	2,19	0,00114	0,009	0,013

5.2 *Pomorskie quay area – neural methods*

In this section the same profiles were analyzed with neural methods. Then statistics for all six survey profiles for Pomorskie quay were calculated for numerical and neural filters.

In figure 4 the same part of the profile as in fig. 3 is presented for neural filters. It can be noticed that the signal is smoothed, yet it follows the changes of heading. Very small fluctuations (about 0,2 degrees) are filtered out. The size of the smoothness can be adjusted with filter parameters and analyzed networks gives similar results.

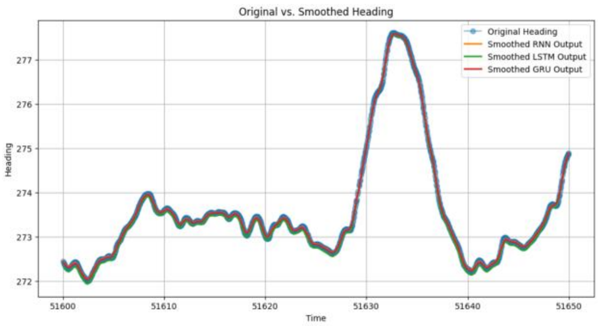

Figure 4. Numerical filtration for gyro heading – selected part of the profile.

It should be however noticed that in case of proposed neural methods, the processing time is higher as each time, iterative training period is needed.

Roughness and smoothness metrics for all analyzed filters (numerical and neural) are given in table 2. These are average values for all analyzed profiles. Interesting observation is that not all metrics are suitable for joint analysis of many profiles. Average standard deviation for all methods is more or less the same, which makes it not useful for such analysis. However SSSD shows good discrimination, while variance of local differences is flatten. MAE and RMSE react similar, however RMSE is more sensitive to variations. Thus, SSSD and RMSE are the metrics to analyze roughness and smoothness of filtered signal.

The analysis of SSSD and RMSE in table 2, shows that numerical filters generally more significantly smooths the signal, except of Holt-Winters filter. Neural filters generally better fits raw data, which results in smaller RMSE. This could be expected, taking into account the background of these filters. Generally, the bast balance was achieved with Whittaker and Gaussian filters in numerical approach and with GRU in neural approach.

Table 2. Average metrics for all analysed profiles and various filters

Method	Standard deviation	SSSD	Variance of local diff.	MAE	RMSE
Raw data	3,323	6,310	0,0033	0,000	0,000
Whittaker filter	3,275	0,011	0,0024	0,066	0,118
Moving average	3,338	0,063	0,0028	0,209	0,362
Gauss filter	3,245	0,007	0,0022	0,105	0,190
Holt-Winters filter	3,325	3,374	0,0032	0,009	0,015
RNN	3,389	0,895	0,0030	0,096	0,107
LSTM	3,399	0,747	0,0030	0,080	0,098
GRU	3,378	0,508	0,0029	0,074	0,081

6 CONCLUSIONS

The paper shows initial research on filtration of heading data during Multibeam Echosounder Surveys. This process is needed as the data many times is affected by temporal inaccuracies and sudden jumps of signal, which affects quality of MBES measurements. In this research we propose to use Machine Learning approach known from time series analysis, using three various neural networks, based on recurrent neural network. For comparison, we also use traditional numerical filtration methods. Real data form the measurements were used for analysis.

The results show that Machine Learning approach can be used for this purpose with good results – better than some numerical methods. However, the drawback of analysed neural network is the need of iterative training for any new dataset. It means that for each profile new network parameters needs to be established, which takes time and efforts. Simultaneously comparatively good results were achieved with some numerical filters, namely Whittaker smoother and Gaussian filter. The neural approach can be in this situation treated as interesting alternative, however for real-time implementations, indicated numerical filters are recommended.

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