Journal homepage: https://itce.com.ua/en

Information Technologies and Computer Engineering **Vol. 21, No. 3. 2024**

Article's History: Received: 30.08.2024 Revised: 12.11.2024 Accepted: 26.12.2024

UDC 621.396.96:534.23

10.63341/vitce/3.2024.77

Correction of roll-caused stripe noise in side scan sonar images

Oleksandr Katrusha*
Postgraduate Student
National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"
03056, 37 Beresteiskyi Ave., Kyiv, Ukraine
https://orcid.org/0009-0008-7097-4843

Abstract. Ensuring high-quality images obtained using side-scan sonar is crucial for enhancing the effectiveness of underwater research, as distortions such as striping noise can complicate data analysis. The aim of this paper was to investigate the nature of striping noise, determine the correlation between image intensity and the tilt of the sonar, and develop a new method to improve the quality of sonar images. The study employed a statistical correction method based on calculating a horizontal moving average for intensity correction, as well as a machine learning model using a three-layer neural network to predict the horizontal moving average considering the beam's incidence angle, the sonar's height above the seafloor, and the initial line intensity. Statistical methods and machine learning techniques were applied to correct the striping noise caused by tilting in sonar images, significantly enhancing their quality. The statistical approach, which uses the mean value of the horizontal sway, effectively reduced noise while preserving critical details and improving overall clarity. The machine learning model incorporated additional parameters, enhancing intensity prediction accuracy and improving adaptability to various sonar positioning conditions. Moreover, the new method accounts for varying environmental conditions, making it flexible and effective for real-world underwater research. These results provide valuable insights for improving sonar image processing methods, paving the way for more efficient underwater exploration and improving the accuracy of object detection on the seafloor

Keywords: seafloor; greyscale; intensity; roll; correction; machine learning; neural network

Introduction

Side scan sonar, a technology widely utilised since the 1950s, plays a crucial role in underwater exploration, supporting various activities such as search and rescue missions, bathymetry, and mine detection. Despite its effectiveness, side scan sonar images are often affected by distortions due to the complex underwater environment and sonar's movement. Among these distortions, stripe noise arising from roll variations compromises image clarity, particularly affecting object recognition and seafloor segmentation. This type of noise manifests as alternating dark and bright stripes across the image, complicating both manual and automated interpretation of sonar data. Addressing stripe noise is a complex task, as existing intensity normalisation methods often fall short in handling roll-induced artefacts. Roll-caused stripe noise is unpredictable and variable in length, width, and frequency due to environmental factors like wave patterns and seafloor profile, which are difficult to standardise in real-time. Therefore, there is a need for targeted correction methods that specifically address roll-induced stripe noise, enhancing the utility of sonar imagery in underwater research and exploration.

Z. Lu *et al*. (2023) investigated a method for enhancing side-scan images based on multistage image restoration and fusion. The aim of the study was to improve image clarity by suppressing noise and correcting uneven illumination. The results showed that the proposed method significantly improves the image quality, which contributes to a better analysis of the seabed. P. Zhou *et al*. (2024) presented a multiscale fusion strategy for correcting side-scan images to improve contrast and reduce the impact of noise. The aim of the study was to improve the accuracy of object detection and eliminate noise in the images. The results proved the effectiveness of the approach for improving the contrast and clarity of details in sonograms.

H. Xia *et al*. (2024) investigated an improved method for removing banding noise based on the Criminisi

Suggested Citation:
Katrusha, O. (2024). Correction of roll-caused stripe noise in side scan sonar images. *Information Technologies and Computer Engineering*, 21(3), 77-85. doi: 10.63341/vitce/3.2024.77

*Corresponding author

algorithm. The aim was to adapt the method for specific noise features in side-scan images. The results showed that the improved method can better cope with multidirectional noise while maintaining the clarity of important structures. The article M. Li *et al*. (2022) presented an approach to removing banding noise in infrared images, based on the sparsity of gradients along the band direction and the global sparsity of noise. An Adaptive Edge-Preserving Operator (AEPO) was proposed, which safeguards edge details in the image while minimising information loss.

J. Guan *et al*. (2019) proposed an innovative wavelet-based deep neural network that effectively removes banding noise in infrared images, taking into account its intrinsic characteristics and the interconnections between wavelet sub-bands. A directional regulariser was added to enhance the separation of scene details from noise, ensuring more accurate image restoration. In the study by S. Shaobo *et al*. (2022), a novel radiometric correction method for side-scan sonar (SSS) images was proposed, incorporating prior knowledge of acoustic illumination and seabed characteristics. The method is based on the decomposition of illumination and albedo components using low-rank constraints and anisotropic total variation (ATV). Experimental results demonstrated the effectiveness of the proposed approach in correcting radiometric distortions and reducing residual noise. It must be noted that little attention was paid in the scientific literature to roll-caused strip noise of sonar images with its peculiarities – sporadicity, variations in length, width and frequency caused by sonar beam pattern and direction of vehicle in relation to waves, strong dependence on floor profile that is typically unknown when using side scan sonar. These characteristics of roll-caused stripe noise make the abovementioned methods hardly applicable to roll-caused stripe noise of side scan sonar images. The purpose of this paper was to investigate the nature of stripe noise, determine the relationship between image intensity and sonar roll angle, and develop a new method for improving the quality of sonar images.

Materials and Methods

This section provides a structured outline of the methods used in this study, including data selection, the analysis of the relationship between image intensity and sonar roll, and the steps in the proposed stripe noise correction methodology. The methodology consisted of two primary approaches: a statistics-based correction method and a machine learning-based model that builds on the results of the initial statistical analysis.

This study analysed more than 300 log files of sonar measurements obtained with the "Sonobot 5" unmanned surface vehicle manufactured by the German company "EvoLogics GmbH". The selection criteria focused on logs with high roll standard deviation and a Pearson's correlation coefficient greater than 0.3 between average along-track image intensity and roll. These criteria ensure that the selected data contain sufficient variability to capture the effects of roll on stripe noise in sonar images.

The roll distribution in the selected missions was close to normal, with a mean of zero. The standard deviation of roll varied across missions, influenced by wave patterns and strength specific to each mission. This distribution allowed for a robust analysis of the relationship between roll and intensity distortion in sonar images (Fig. 1).

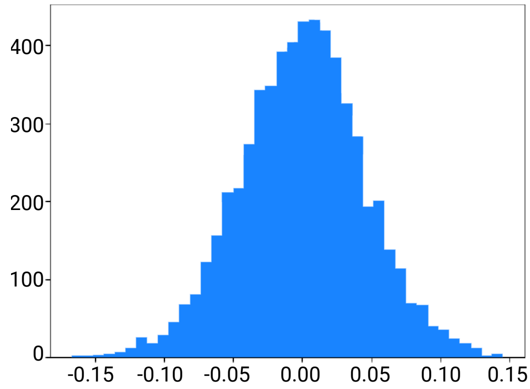

Figure 1. Typical distribution of vehicle roll in Rad
Notes: X-axis is roll angle in Rad, Y-axis – number of observations
Source: created by the author

A visual inspection of the sonar images revealed a clear relationship between roll and stripe noise. As shown in Figure 2, negative roll angles corresponded to darker areas on the left side of the image, likely due to the sonar transmitter's left main lobe ensonifying regions closer to the sonar. Conversely, positive roll angles produced darker areas on the right side of the image, suggesting a mirrored pattern. This pattern, as illustrated in Figure 3, demonstrates the dependency of intensity on roll but also highlights that this relationship is modulated by additional factors such as sonar altitude and seafloor topography. Consequently, a straightforward intensity correction approach was deemed insufficient, necessitating a more comprehensive correction method.

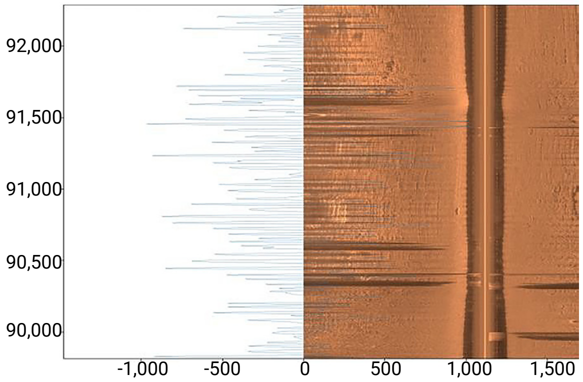

Figure 2. A fragment of a striped sonar image with corresponding roll in Rad ×10,000 (blue line). Sonar vehicle movement is bottom-upd
Notes: X-axis is roll angle in Rad ×10,000, Y-axis – ping number
Source: created by the author

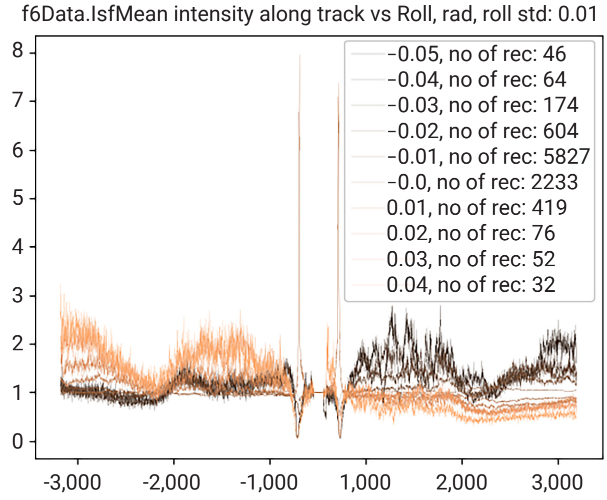

Figure 3. Average intensities of image parts depending on roll vs average intensity of the image

Notes: the X-axis is the slant range (negative on port side), and the Y-axis is the ratio between average intensity for roll angle and average along-tack intensity of the whole image. The number of records for each rounded roll angle is displayed in the legend. Roll angles with fewer than 30 records are considered outliers and are not displayed

Source: created by the author

The proposed methods included a statistics-based correction method and a machine learning-based model. The statistics-based approach involves a statistical analysis aimed at establishing a baseline correction by calculating a horizontal rolling mean, which adjusts intensity variations that correlate with roll angle. The machine learning-based model, building on the initial statistical analysis, utilises a three-layer dense neural network to predict the horizontal rolling mean for sonar images. This model takes roll, altitude, and original line intensity as inputs and outputs a corrected horizontal mean, simulating an image with zero roll influence.

A dataset of 40,000 samples was derived from ten representative sonar images, where the inputs consist of roll, altitude, and line intensity, and the output is the horizontal rolling mean. The model was trained using TensorFlow with the ADAM optimiser, over 800 epochs, with a batch size of 256. The training was conducted on hardware that included a GeForce RTX4070 graphics processing unit and an Intel i-Core 7 central processing unit, taking approximately 40 minutes, while inference on a 2,200×20,000 pixel image required about 300 milliseconds. Formula (1) describes the training stage, where d is altitude, φ is roll, *Lo* – line intensity of the original image and *Mh* – line horizontal mean:

$$d, \phi, Lo => Mh. \tag{1}$$

The formula is used to generate predictions for the horizontal average line intensity based on the specified input parameters. This allows to adjust the signal intensity in images, reducing distortion caused by roll variations and altitude changes.

Results and Discussion

Sonar technology operates by emitting a series of sound impulses that travel through water and reflect off underwater objects and the seafloor. The intensity of these reflected signals is then recorded, allowing for the construction of sonar images, commonly referred to as sonograms. Each sonogram is created by sequentially adding lines of received signal intensity, resulting in a comprehensive visual representation of the underwater environment.

The process of sonar imaging is inherently influenced by various factors that can lead to geometrical and intensity distortions. The complex physical laws governing sound reflection and propagation in water play a crucial role in how sonar signals behave. For example, the angle of incidence, the type of materials on the seafloor, and the acoustic properties of the water can all affect how sound waves are reflected back to the sonar device. The movement of the sonar vehicle, including its speed and direction, can introduce further variability into the recorded data (Ye *et al.*, 2019). Underwater currents also contribute to the challenges faced during sonar imaging. They can alter the trajectory of the sound waves, leading to inconsistencies in the intensity of the returned signals. This variability can result in images that are less readable, making it difficult to accurately detect and classify objects on the seafloor. Both human operators and machine learning algorithms face significant hurdles when attempting to interpret these distorted images, as the noise and artifacts can obscure critical features of the underwater landscape (Capus *et al.*, 2008; Al-Rawi *et al.*, 2017).

Variations by roll do not affect image geometry directly but can cause intensity distortion caused by uneven ensonification of different seafloor areas due to non-uniformity of sonar beam pattern. Figure 4 illustrates the convention of Euler angles that define roll (φ) among other angles. J.E. Hughes Clarke (2004) provide a sample empirically derived beam pattern of a side scan sonar (Fig. 5).

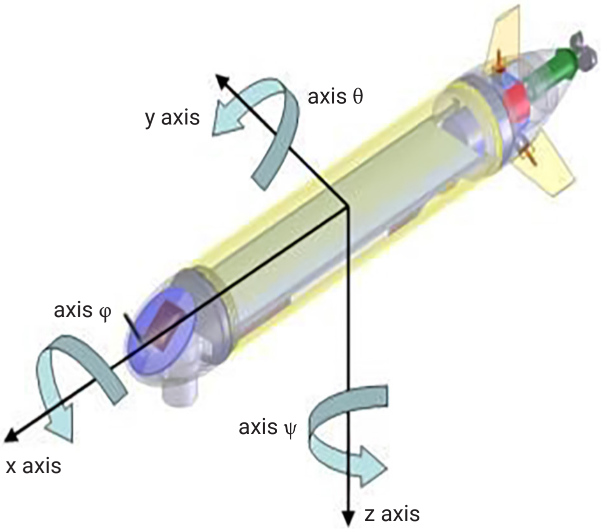

Figure 4. The body-fixed reference frame and Euler angles

Source: Navigation messages (n.d.)

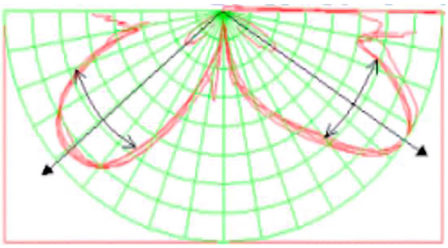

Figure 5. Empirically derived beam pseudo-pattern of a side scan sonar
Source: J.E. Hughes Clarke (2004)

The roll-caused intensity distortion, commonly referred to as stripe noise, can be observed as a series of alternating dark and bright stripes across the image, each with varying length and width and a distinct periodic pattern. These stripes tend to widen toward the edges of the image and exhibit asymmetry in brightness, with darker stripes on one side corresponding to brighter ones on the opposite side. In regions of acoustic shadow, stripe noise is typically less visible or absent altogether. An example of roll-caused intensity distortion also known as stripe noise can be seen in Figure 6. It appears as sporadic series of alternating dark and bright across track stripes of various length and width with distinct periodic pattern.

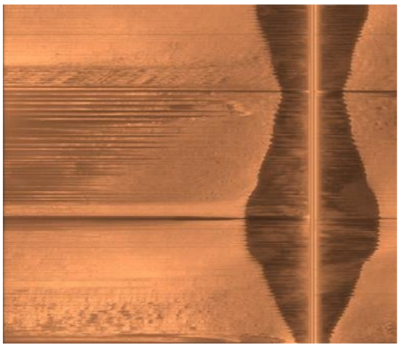

Figure 6. An example of stripe noise on a sonogram. Sonar vehicle movement bottom-up
Source: created by the author

The main cause of stripe noise in the provided examples is the influence of wave motion on the keel-mounted sonar, which induces variations in roll that affect seafloor ensonification due to non-uniformity of the beam pattern and the resulting image intensity. In general terms, the objective of roll-caused stripe noise correction is to restore the intensity profile of each scanned line as if it were captured at a zero roll angle. However, in certain extreme cases, valuable seafloor information can be entirely obscured by overly dark or bright sections, making full restoration impractical.

Correction based on rolling mean

To address this, a statistical-based approach to stripe noise correction was initially implemented. For each horizontal line in the image, a horizontal rolling mean was calculated to help identify the underlying intensity trend across the track while minimising random noise. The window size for the rolling mean was empirically determined to balance smoothness and data retention, ensuring that subtle seafloor features were not lost. Subsequently, this horizontal mean was averaged along-track to generate a neighbourhood mean, providing a contextual baseline for each line. The window size for this averaging process corresponds to the maximum periodicity of the stripe noise, approximately 20 lines or two meters on the seafloor in this dataset. This period closely matches the average period of wave-induced roll variations, making it a suitable reference for noise correction.

Rolling mean was chosen over interpolation and other smoothing techniques due to its computational efficiency and ease of implementation. Empirical analysis confirmed that this approach effectively reduces the noise without compromising the critical details of the image.

Figure 7 shows the process of image correction using the rolling mean method. Figure 7(a) shows the original image, which contains striped noise caused by variations in the roll of the sonar instrument. Figure 7(b) shows the correction map obtained by dividing the horizontal average by the average of the neighbouring lines. In the correction map, red indicates higher values and blue indicates lower values. This map fits the stripe noise well, although it does not directly account for roll variation. Figure 7(c) shows the result of the image correction, where the correction map is applied to the original image.

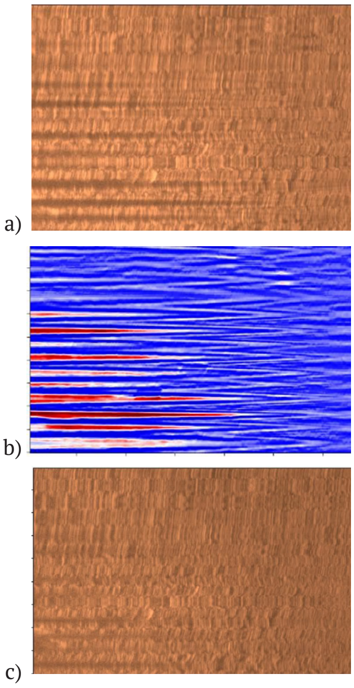

Figure 7. The process of stripe noise correction in sonar images using the moving average method
Notes: a) a piece of original image with stripe noise; b) correction map based on rolling mean (red colour corresponds to higher values, blue colour – to lower ones); c) correction result
Source: created by the author

Through the process of image correction, the stripe noise is reduced and the image becomes clearer. A correction map is obtained by dividing the horizontal mean by neighbourhood mean (Fig. 7(b)). As it can be seen from the figure, the correction map corresponds well to stripe noise, although does not take roll variations into account directly. Then correction procedure for every horizontal line can be implemented as in Formula (2):

$$L_c = L_o - M_h + M_h \times C_i, \tag{2}$$

where L_c – corrected horizontal line of the image; L_o – original line; M_h – calculated horizontal mean for the line; C_i – corresponding line of the correction map.

The rolling mean method is simple, computationally effective, and easy in implementation, but it is based solely on image information. Whereas intensity of the image pixel depends, among others, on the following parameters: slant range, floor profile, floor sediment type, incidence angle, roll, sonar beam pattern and sonar altitude (Al-Rawi, 2016; Chang *et al.*, 2020). Failure to take account for these factors can lead to overcompensation in some areas, loss of acoustic shadows and periodic seafloor patterns, wrong compensation of the areas with high floor gradient.

Correction using neural network inference

To enhance the correction process by incorporating additional parameters, such as roll and altitude, a machine learning-based method is introduced. Machine learning techniques are increasingly applied to sonar image processing, including tasks such as object detection, feature extraction, classification, and seafloor segmentation (Chen *et al.*, 2017; Li *et al.*, 2024). However, due to the relatively high cost and limited availability of sonar data, these methods lag behind traditional optical computer vision techniques. Most current research focuses on improving object depiction and seafloor clarity, yet few studies have specifically targeted stripe noise correction (Steiniger *et al.*, 2022; Sivachandra & Kumudham, 2024).

The proposed machine learning model aims to predict the intensity dependence by approximating the rolling mean of image intensity based on variables including roll, slant range, altitude, and floor profile. This approach avoids the need for complex mathematical models, such as Lambertian reflections, by training the model to infer these relationships from available data. This setup is especially useful in sonar applications where obtaining ground-truth images is costly and often infeasible.

The limited availability and high cost of obtaining ground truth data present significant challenges for most machine learning approaches in sonar applications. Consequently, directly training models using pairs of distorted and corrected images is often impossible. These algorithms possess the capability to approximate the dependencies of intensity based on various parameters, which can be leveraged to address this issue effectively. The proposed method involves using a neural network to model the complex relationship between the intensity rolling mean and variables such as roll, slant range, altitude, and floor profile, without relying on intricate mathematical models like the Lambertian law.

Due to the limited availability and high cost of obtaining ground truth data, most machine learning approaches in sonar applications face significant challenges. This approach allows for more flexible modelling of intensity dependencies, accommodating the unique characteristics of sonar data.

To correct stripe noise, the subsequent inference stage (3), where *Mc* is the inferred horizontal mean, predicts the horizontal rolling mean for the lines with the same inputs, except for roll, which is set to zero radians. This formula is derived from (1), providing a baseline adjustment in the absence of roll effects (3):

$$d, 0, Lo = >Mc. \tag{3}$$

Then, based on this correction, the following formula is applied (4):

$$I_c = I_o - M_h + M_c, \tag{4}$$

where I_c – corrected image; I_o – original image; M_h – horizontal mean; M_c – correction value.

Correction map is constructed as a difference between the inferred rolling mean and original rolling mean. After that correction map is subtracted from the original image thus correcting the roll-caused variation (4). For the experiment, a simple three-layer dense neural network was used. It took roll, altitude, original line intensity as input and horizontal rolling mean as output. The training set of 40,000 samples was generated from ten sonar images. The inference stage is aimed at predicting the horizontal mean with zero roll.

Figure 8 illustrates the effectiveness of the neural network in capturing the relationship between roll and mean intensity, as evidenced by the corrected images. Panel (a) displays the original image with pronounced stripe noise, while panel (b) presents the correction map generated through inference. The correction map indicates higher values in red and lower values in blue, highlighting areas where the neural network has identified the need for adjustment. The resulting corrected image is shown in panel (c), demonstrating noticeable improvements in clarity.

Despite the success in modelling this dependency, instances of overcompensation and excessive smoothing of the image were observed with the application of the inferred correction map. This phenomenon suggests that while the model effectively learned certain aspects of the intensity relationship, it may not have fully accounted for all complexities inherent in sonar imagery. Such overcompensation can obscure fine details and alter important features of the seabed, potentially complicating subsequent analysis.

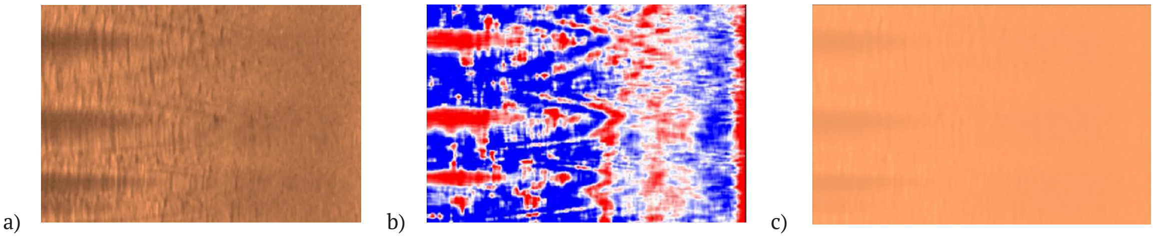

Figure 1. Neural network-based correction of stripe noise in sonar images
Notes: a) original image with stripe noise; b) correction map based on inference (red colour corresponds to higher values, blue colour – to lower ones); c) corrected image
Source: compiled by the author

To address these issues, incorporation of additional features into the training process is proposed. For instance, including derivatives of intensity values, various angles, and their mean values, as well as information from adjacent image lines, could enhance the model's capacity to capture more nuanced relationships. Further experimentation with neural network architecture, including adjustments to layer configurations and activation functions, may also yield better results. These refinements will be the focus of future research, with the aim of improving the model's robustness and accuracy in correcting stripe noise, ultimately leading to enhanced sonar image quality and reliability in underwater exploration.

The discourse surrounding the correction of roll-caused stripe noise

The findings of this study resonate with the studies of other researchers in the field, highlighting a shared commitment to improving sonar image quality through various correction methodologies. For instance, Y.-C. Chang *et al*. (2020) focused on processing side-scan images to correct brightness variation and fill gaps, aiming to eliminate problems associated with uneven illumination during seabed scanning. They developed a technique that improves image quality, resulting in a more homogeneous representation of the seabed. Their results demonstrated that this method effectively reduces luminance distortions and increases the convenience of further image analysis. Previous studies have also investigated various approaches to noise reduction, including advanced filtering techniques and optimisation algorithms specifically designed for sonar data. Research has highlighted the potential of deep learning models to improve object detection and seafloor classification, underscoring the importance of leveraging multiple methodologies to address the challenges posed by sonar imagery. These collective efforts emphasise the significance of a multi-faceted approach to improving sonar data processing, suggesting that continued collaboration and innovation in this field are essential for advancing underwater exploration and analysis.

M.S. Al-Rawi (2016) developed an intensity normalisation method specifically for side-scan sonar images, which targeted the elimination of brightness irregularities arising from changes in the angles of sound wave incidence. Their research demonstrated that these irregularities could significantly impact the clarity of sonar images, making it challenging to identify and analyse underwater features accurately. By implementing their normalisation technique, authors found that distortion was effectively reduced, leading to enhanced object recognition capabilities in sonar images. This study underscored the critical importance of addressing intensity variations to improve the overall utility of sonar technology in underwater applications.

J. Zhao *et al*. (2017) introduced a radiometric correction method that considers the variation of sediment types on the seafloor, which can significantly influence how sonar signals are reflected back to the device. Their study provided a comprehensive model that accounted for the different acoustic properties of various sediment types, thereby enhancing the accuracy and detail of the reflected signal intensity data. By integrating sediment characteristics into their correction methodology, J. Zhao *et al*. were able to achieve more reliable and detailed sonar images, which are essential for effective seafloor mapping and analysis.

The findings of this study align with and build upon the results of several notable researchers in the field of sonar image processing. A. Burguera & G. Oliver (2014) focused on intensity correction to mitigate uneven illumination effects, which ultimately improved image quality and facilitated better data analysis. Similarly, the current research successfully addressed stripe noise through a correction methodology that enhances image clarity, demonstrating a parallel objective of improving the usability of sonar imagery for analysis.

G. Shippey *et al*. (1994) applied a shadow correction method utilising histogram transformations to enhance the contrast and detail in side-scan sonar images. Their approach specifically targeted the reduction of uneven brightness, a common challenge that can obscure essential features and hinder effective seabed analysis. By creating more homogeneous images, their methodology not only improved the visibility of underwater structures but also facilitated more accurate object detection and classification. The results from this study resonate with the current findings, where the application of neural network techniques and rolling mean methods also aims to enhance overall image quality and facilitate clearer object recognition. Both approaches underscored the importance of addressing brightness inconsistencies in sonar imagery to achieve better analytical outcomes.

D. Wilken *et al*. (2012) applied Fourier filtering in two-dimensional space to eliminate stripe noise in mosaics of side-scan images. The goal was to reduce periodic noise and improve the quality of the mosaic images of the seafloor. The results showed that Fourier filtering effectively eliminates bandpass noise and produces more homogeneous and clear images.

Y. Chen *et al*. (2017) developed a method for removing stripe noise in remote sensing images through total variation regularisation and group sparsity constraints. Their research highlighted the effectiveness of this approach in yielding clearer and more detailed images, reinforcing the objective of the present research, which focuses on removing stripe noise and enhancing the quality of sonar data processing.

An analysis of these studies indicated a prevailing trend in the adoption of advanced correction techniques, whether through statistical methods, machine learning, or mathematical modelling, to improve the quality of sonar images. The integration of these methodologies reinforces the notion that a multi-faceted approach is essential for effectively addressing the challenges of sonar data processing. The findings from this research not only contribute to the existing body of knowledge but also suggest that further refinement and innovation in correction techniques will continue to play a crucial role in advancing underwater exploration and analysis.

Conclusions

In this study the nature of roll-caused stripe noise of sonar images was analysed. Clear dependency and correlation between stripe noise and roll angle variation has been shown. Statistical rolling mean approach and a simple approach based on machine learning methods were proposed to compensate stripe noise on sonar images and to enhance image quality. The statistical analysis established a foundational correction technique by calculating the horizontal rolling mean, which effectively mitigated random noise while preserving critical details of the sonar images. This method demonstrated its utility in reducing the visual impact of stripe noise, resulting in clearer images that facilitate better object detection and seafloor analysis. However, recognising the limitations of the rolling mean method, particularly its reliance on image data alone, the introduction of a machine learning-based model marked a significant advancement. By incorporating additional parameters such as roll, slant range, altitude, and floor profile, the neural network effectively captured the complex dependencies of image intensity. This approach not only enhanced the correction accuracy but also provided a more adaptable framework for addressing varying sonar conditions.

The results indicated that while both methods improve the quality of sonar images, the machine learning model offers a more robust solution by accommodating external factors that influence intensity. The findings contributed valuable insights into improving sonar image processing, paving the way for more effective underwater exploration and research. The methodologies outlined herein can serve as a foundation for future studies aimed at further refining noise correction techniques in sonar applications.

Future research in this direction will include improvement of the machine learning algorithm to avoid overcompensation of non-striped areas. Development of more universal algorithms and ML models that can incorporate additional features like difference between image lines, sonar type, it's beam pattern, sediment type and others that can potentially lead to development of simple, fast, and universal stripe noise correction method. The benefits of machine learning methods are their universality, relatively simple implementation, and quick inference. It makes them suitable for real time or bulk sonar image correction and processing.

Acknowledgements

The author expresses his gratitude to EvoLogics GmbH for the provided data and support of this research and also grateful to the Armed Forces of Ukraine for their service.

Conflict of Interest

None.

References

[1] Al-Rawi, M., Galdran, A., Isasi, A., & Elmgren, F. (2017). Cubic spline regression based enhancement of side-scan sonar imagery. In *Proceedings of the OCEANS 2017* (pp. 1-7). Aberdeen: Institute of Electrical and Electronics Engineers. doi: 10.1109/oceanse.2017.8084567.

[2] Al-Rawi, M.S. (2016). Intensity normalization of sidescan sonar imagery. In *Proceedings of the international conference on image processing theory, tools and applications* (pp. 1-6). Oulu: IEEE. doi: 10.1109/IPTA.2016.7820967.

[3] Burguera, A., & Oliver, G. (2014). Intensity correction of side-scan sonar images. In *Proceedings of the emerging technology and factory automation* (pp. 1-4). Barcelona: Institute of Electrical and Electronics Engineers. doi: 10.1109/ETFA33519.2014.

[4] Capus, C.G., Banks, A.C., Coiras, E., Tena Ruiz, I., Smith, C.J., & Petillot, Y.R. (2008). Data correction for visualisation and classification of sidescan SONAR imagery. *IET Radar, Sonar & Navigation*, 2(3), 155-169. doi: 10.1049/iet-rsn:20070032.

[5] Chang, Y.-C., Hsu, S.-K., & Tsai, C.-H. (2020). Sidescan sonar image processing: Correcting brightness variation and patching gaps. *Journal of Marine Science and Technology*, 18(6), 721-730. doi: 10.51400/2709-6998.1935.

[6] Chen, Y., Huang, T.-Z., Zhao, X.-L., Deng, L.-J., & Huang, J. (2017). Stripe noise removal of remote sensing images by total variation regularization and group sparsity constraint. *Remote Sensing*, 9(6), article number 559. doi: 10.3390/rs9060559.

[7] Guan, J., Lai, R., & Xiong, A. (2019). Wavelet deep neural network for stripe noise removal. *IEEE Access*, 7, 44544-44554. doi: 10.1109/ACCESS.2019.2908720.

[8] Hughes Clarke, J.E. (2004). Seafloor characterization using keel-mounted sidescan: Proper compensation for radiometric and geometric distortion. In *Canadian hydrography conference 2004* (pp. 1-18). Ottawa: Hydro International.

[9] Li, M., Nong, S., Nie, T., Han, C., Huang, L., & Qu, L. (2022). A novel stripe noise removal model for infrared images. *Sensors*, 22(8), article number 6971. doi: 10.3390/s22082971.

[10] Li, M., Rieck, J., Noheda, B., Roerdink, J., & Wilkinson, M. (2024). Stripe noise removal in conductive atomic force microscopy. *Scientific Reports*, 14(1), article number 3931. doi: 10.1038/s41598-024-54094-w.

[11] Lu, Z., Zhu, T., Zhou, H., Zhang, L., & Jia, C. (2023). An image enhancement method for side-scan sonar images based on multi-stage repairing image fusion. *Electronics*, 12(17), article number 3553. doi: 10.3390/electronics12173553.

[12] Navigation Messages. (n.d.). Retrieved from https://www.lsts.pt/docs/imc/master/Navigation.html.

[13] Shaobo, S., Jianhu, L., Yongcan, Y., Yunlong, W., Shaofeng, B., & Guojun, Z. (2022). Anisotropic total variation regularized low-rank approximation for SSS images radiometric distortion correction. *IEEE Transactions on Geoscience and Remote Sensing*, 60, article number 5925412. doi: 10.1109/TGRS.2022.3229301.

[14] Shippey, G., Bolinder, A., & Finndin, R. (1994). Shade correction of side-scan sonar imagery by histogram transformation. In *Proceedings of the OCEANS'94* (pp. 439-443). Brest: Institute of Electrical and Electronics Engineers. doi: 10.1109/OCEANS.1994.364084.

[15] Sivachandra, K., & Kumudham, R. (2024). A review: Object detection and classification using side scan sonar images via deep learning techniques. In V.K. Gunjan, J.M. Zurada, N. Singh (Eds.), *Modern approaches in machine learning and cognitive science: A walkthrough* (pp. 229-249). Cham: Springer. doi: 10.1007/978-3-031-43009-1_20.

[16] Steiniger, Y., Kraus, D., & Meisen, T. (2022). Survey on deep learning based computer vision for sonar imagery. *Engineering Applications of Artificial Intelligence*, 114, article number 105157. doi: 10.1016/j.engappai.2022.105157.

[17] Wilken, D., Feldens, P., Wunderlich, T., & Heinrich, C. (2012). Application of 2D Fourier filtering for elimination of stripe noise in side-scan sonar mosaics. *Geo-Marine Letters*, 32(4), 337-347. doi: 10.1007/s00367-012-0293-z.

[18] Xia, H., Cui, Y., Jin, S., Bian, G., Liu, G., Zhang, W., & Peng, C. (2024). Improvement of Criminisi's stripe noise suppression method for side-scan sonar images. *Applied Sciences*, 14(20), article number 9574. doi: 10.3390/app14209574.

[19] Ye, X., Yang, H., Li, C., Jia, Y., & Li, P. (2019). A gray scale correction method for side-scan sonar images based on Retinex. *Remote Sensing*, 11(11), article number 1281. doi: 10.3390/rs11111281.

[20] Zhao, J., Yan, J., Zhang, H., & Meng, J. (2017). A new radiometric correction method for side-scan sonar images in consideration of seabed sediment variation. *Remote Sensing*, 9(6), article number 575. doi: 10.3390/rs9060575.

[21] Zhou, P., Chen, J., Tang, P., Gan, J., & Zhang, H. (2024). A multi-scale fusion strategy for side scan sonar image correction to improve low contrast and noise interference. *Remote Sensing*, 16(10), article number 1752. doi: 10.3390/rs16101752.

Корекція смугового шуму, спричиненого креном, на зображеннях гідролокатора бокового огляду

Олександр Катруша[*]
Аспірант
Національний технічний університет України
«Київський політехнічний інститут імені Ігоря Сікорського»
03056, просп. Берестейський, 37, м. Київ, Україна
https://orcid.org/0009-0008-7097-4843

Анотація. Забезпечення високої якості зображень, отриманих за допомогою гідролокатора бокового огляду, є важливим для підвищення ефективності підводних досліджень, оскільки такі спотворення, як смуговий шум, можуть ускладнювати аналіз даних. Мета цієї статті – дослідити природу смугового шуму, визначити кореляцію між інтенсивністю зображення і крену гідролокатора, а також розробити новий метод покращення якості гідролокаційних зображень. У дослідженні використовується метод статистичної корекції, заснований на розрахунку горизонтальної ковзної середньої для корекції інтенсивності, а також модель машинного навчання, яка використовує тришарову нейронну мережу для прогнозування горизонтальної ковзної середньої з урахуванням кута падіння променя, висоти гідролокатора над дном та початкової інтенсивності лінії. У дослідженні було застосовано статистичні методи та методи машинного навчання для корекції смугового шуму, спричиненого кренуванням, на гідролокаційних зображеннях, що значно покращило їх якість. Статистичний підхід, що використовує середнє значення горизонтальної хитавиці, ефективно зменшив шум, зберігши при цьому критичні деталі і підвищивши загальну чіткість. Модель машинного навчання включала додаткові параметри, що підвищило точність прогнозування інтенсивності та покращило адаптивність до різних умов положення гідролокатора. Крім того, новий метод дозволяє враховувати змінні умови на місцевості, що робить його гнучким і ефективним в умовах реальних підводних досліджень. Ці результати дають цінну інформацію для вдосконалення методів обробки гідролокаційних зображень, прокладаючи шлях до більш ефективної підводної розвідки та покращення точності виявлення об'єктів на дні моря

Ключові слова: морське дно; відтінки сірого; інтенсивність; крен; корекція; машинне навчання; нейронна мережа