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INTENSITY CORRECTION IN SIDE SCAN SONAR IMAGES. METHODS OVERVIEW

The use of sonars, particularly side-scan sonars, in underwater research dates back to the mid-20th century. Due to their relative affordability, ease of operation, and high efficiency in seabed visualization, these devices have become indispensable tools in hydrography, marine archaeology, environmental monitoring, and search-and-rescue operations. However, the processing of sonar images (sonograms) presents a number of challenges caused by signal distortions. The main types of such artifacts include intensity non-uniformities, stripe noise, geometric distortions, and residual effects of imperfect time-based intensity compensation. Given the complexity of acoustic propagation in underwater environments and the variability of sensor configurations, there is currently no universal method for intensity correction that performs effectively across all scenarios. This study presents a structured review of existing methods for correcting intensity in side-scan sonar images developed over recent decades. Emphasis is placed on their algorithmic implementation, suitability for real-time processing, and effectiveness in constructing high-quality sonar mosaics. Particular attention is paid to the analysis of the causes of intensity variation, including the phenomenon of brightness falloff across the swath, repetitive stripe noise, time-varying gain, and residual intensity anomalies in the time domain. The review covers a range of models and approaches, including empirical smoothing techniques, multivariate regression, local normalization, hybrid filtering strategies, and methods based on physical models of acoustic scattering. A proposed classification framework allows for the organization of these approaches according to several criteria: model type (empirical, physical, machine learning), underlying assumptions, constraints under real-world conditions, and the types of metrics used for quality evaluation. The potential of each method to be adapted for tasks such as automatic object detection and the construction of accurate seafloor morphology models is also explored. This material may be valuable both for engineering practitioners involved in applied sonar processing and for researchers seeking advanced algorithms for sonogram enhancement and develop adaptive computer vision systems for complex underwater environments.

Key words: *side-scan sonar, sonogram, intensity correction, sonar mosaic, stripe noise, digital signal processing, adaptive algorithms, deep learning, computer vision.*

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КОРЕКЦІЯ ІНТЕНСИВНОСТІ ЗОБРАЖЕНЬ СОНАРА БОКОВОГО ОГЛЯДУ. ОГЛЯД МЕТОДІВ

Використання сонарів, зокрема сонарів бокового огляду, у підводних дослідженнях бере свій початок із середини XX століття. Завдяки своїй відносній дешевизні, простоті експлуатації та високій ефективності у візуалізації морського дна, ці пристрої стали невід'ємним інструментом гідрографії, морської археології, екологічного моніторингу та пошуково-рятувальних операцій. Однак обробка сонограм супроводжується низкою складнощів, зумовлених спотвореннями сигналу. До основних типів таких артефактів належать неоднорідності інтенсивності, смуговий шум, геометричні викривлення та залишкові наслідки недосконалої компенсації часової залежності сигналу. Враховуючи складність акустичних властивостей середовища та варіативність конфігурацій сенсорів, універсального методу корекції інтенсивності, який був би ефективним у всіх сценаріях, наразі не існує. У цьому дослідженні представлено систематизований огляд існуючих методів корекції інтенсивності зображень сонара бокового огляду, що були розроблені впродовж останніх десятиліть. Акцент зроблено на їхню алгоритмічну реалізацію, застосовність у реальному часі та ефективність у контексті побудови високоякісних сонарних мозаїк. Особливу увагу приділено аналізу причин виникнення варіацій інтенсивності, зокрема феномену *спадання яскравості поперек напряму руху носія, повторюваним смуговим шумам і залишковим артефактам корекції інтенсивності у часовому домені. Розглянуто низку моделей та підходів, серед яких емпірічні згладжувальні методи, багатовимірна регресія, локальна нормалізація, гібридні фільтраційні стратегії та методи на основі фізичних моделей акустичного розсіювання. Запропонована класифікаційна схема дозволила структурувати відомі підходи за критеріями: тип моделі (емпірична, фізична, машинне навчання), вихідні припущення, обмеження в умовах реального застосування, а також тип використовуваних метрик для оцінки якості обробки. Окремо розглянуто потенціал кожного методу щодо адаптації до задач автоматичного розпізнавання об'єктів та побудови точних морфологічних моделей дна. Матеріал може бути корисним як для інженерів-практиків, що займаються прикладною обробкою сонарних зображень, так і для дослідників, зацікавлених у подальшому розвитку алгоритмів покращення якості сонограм та створенні адаптивних систем з комп'ютерним зором для роботи у складних підводних умовах.*

Ключові слова: *сонар бокового огляду, сонограма, корекція інтенсивності, сонарна мозаїка, смуговий шум, цифрова обробка сигналів, адаптивні алгоритми, глибинне навчання, комп'ютерний зір.*

Problem Statement

In the context of expanding maritime autonomy and the urgent need for scalable, low-cost methods of seafloor imaging and underwater situational awareness, side-scan sonar (SSS) has emerged as a foundational technology across civil, scientific, and defense applications. Its ability to deliver wide-area acoustic coverage with high spatial resolution makes it essential for seabed mapping, marine archaeology, habitat monitoring, infrastructure inspection, and mine detection missions [1]. However, the practical utility of SSS data is critically constrained by the instability of sonar signal intensity, which is influenced by distance, incidence angle, seafloor texture, sediment composition, beam directivity, and sound frequency [2]. These factors cause significant spatial and temporal intensity variation, leading to radiometric inconsistencies such as across-track falloff, stripe noise, and residual artefacts from time-based gain correction. As a result, downstream tasks such as mosaicking, automated object detection, and semantic interpretation are adversely affected.

The problem is further compounded by the operational shift toward autonomous platforms such as AUVs, which require onboard, real-time image enhancement to support navigation, SLAM, and situational response. In such settings, empirical correction models and fixed-parameter filters – commonly used to compensate for signal degradation – fail to adapt to rapidly changing environmental and vehicle conditions, resulting in unstable performance and geometric distortions [3]. Moreover, most classical correction techniques do not scale well with modern mission constraints, where power, memory, and compute resources are limited and mission duration is long.

Consequently, the applied scientific challenge lies in developing intensity correction strategies that account for the non-linearity and dynamism of underwater acoustic propagation, while enabling robust real-time integration into low-power embedded systems. The potential of hybrid methods – combining physical acoustic modeling, contextual metadata from mission logs, and lightweight machine learning – opens a pathway toward improved radiometric fidelity, more accurate object segmentation, and more efficient data fusion with other sensing modalities [4]. There is thus a pressing need for signal-processing solutions that treat radiometric correction not as a secondary enhancement task but as a mission-critical component of sonar-based perception pipelines in complex, variable underwater environments.

Analysis of Recent Studies and Publications

Current challenges in processing and radiometric correction of side-scan sonar (SSS) imagery are addressed in the works of P. Blondel, A. Grządziel, Y. Zhang, X. Ye, J. Zhao, S. Li, A. Burguera, C. Capus, and J. Clarke. These studies examine a broad spectrum of intensity-formation issues, ranging from sensor-resolution effects and acoustic-shadow artefacts to seabed composition and propagation physics. The papers by Zhang et al. and Ye et al. compare contrast-enhancement and brightness-correct algorithms that employ Retinex models and adaptive smoothing over rugged topography, while Zhao, Liu and co-authors focus on compensating intensity variations driven by sediment heterogeneity and complex bottom morphology. Other researchers – particularly Burguera, Capus, and Clarke – propose integrated frameworks that jointly address geometric and radiometric distortions under real-world conditions, from towed arrays to AUV-mounted systems, and discuss normalisation techniques that support reliable classification and the construction of radiometrically uniform acoustic mosaics. Despite these advances, most publications tackle isolated facets – such as stripe-noise filtering or single-pass intensity levelling in controlled environments – leaving the overarching problem of a universal, environment-adaptive correction algorithm, suitable for real-time onboard execution on autonomous underwater platforms, largely unresolved and in need of further systematic investigation.

The aim of this study is to provide a structured and comprehensive analysis of publicly available intensity correction methods for side-scan sonar (SSS) imagery. The research focuses on identifying the underlying models and conceptual approaches, evaluating their theoretical assumptions, implementation complexity, and real-time applicability, as well as exploring potential secondary outputs such as improved contrast, noise suppression, or radiometric normalization.

This methodological review is motivated by the practical demands of underwater imaging and is intended to support engineers and researchers developing sonar data-processing pipelines or seeking directions for further investigation. Given that many commercial solutions are protected by intellectual property rights and confidentiality agreements, the study is deliberately limited to sources from open-access scientific literature. No experimental evaluation or direct benchmarking of specific methods was conducted, as the emphasis is placed on comparative methodology rather than empirical performance.

Results

The signal strength of the reflected underwater sound signal has complex dependency on many factors: spherical spreading of acoustic waves reversely proportional to fourth square of range [1], sound attenuation in water and in sediment, grazing angle, floor profile, sediment type, other factors like water temperature, pressure, salinity, chemical composition of water or water currents. From the sonar or vehicle side the factors include sonar geometry, altitude, beam pattern, calibration and setup, working frequency, sonar movement (roll, pitch, yaw, heave). Acoustic shadows and reverberations also contribute to different intensity variations. For a comprehensive description and mathematical modeling of sound propagation see [1, 11]. This makes it difficult to separate backscatter information about the object of interest (floor profile, object) from other factors. Therefore, the main aim of intensity correction methods is to compensate for unwanted decay in intensity, while preserving valuable information about seafloor characteristics. The intensity of the emitted signal is not uniform by direction and depends on the grazing angle (for terminology see, for example, [12]) due to the physics of sonar construction. Main and side lobes of a sonar form a beam pattern that contributes to sonogram intensity variations. This non-uniformity is a reason for over- or under-ensonification of some areas as well as stripe noise due to sonar rolling. Beam patterns can either be modeled theoretically [13], measured empirically based on sonogram data [14], or related beam function [15] derived and used for intensity correction afterwards.

Dynamic range of side scan sonar can reach more than 100 dB [10] due to the above-mentioned reasons making sonogram unreadable as-is recorded by the sonar. For this reason sonars and processing software employ a time-varied gain (TVG) function that compensates sound decay to reduce the dynamic range to around 40 dB [16] and compose a more uniform and readable sonar image using logarithmic or another approximation [5, 1]. In general case TVG parameters must be carefully selected for the sediment type, floor depth and other factors to compensate for sound attenuation more adequately. Unfortunately, TVG is often implemented on hardware level with little or no possibility of adjustment and therefore does not account for other factors that may need compensation. Moreover, the function itself may contain irregularities that bring additional distortion to intensity [17]. Thus, additional compensation of its residuals affecting SSS images may be needed [18, 19, 20].

Different variation types require different methods of correction. Most of the reviewed methods tackle the first problem. The second type has little coverage in literature, although some authors claim [9] to have compensated for it as well. Mosaic stripe noise is addressed in [21] using 2D Fourier transformation. Most of the reviewed methods address across-track intensity decay (Fig. 1), which is the most common and well-documented type of variation. The near-nadir overexposure and stripe artefacts illustrated in Fig. 2 are less frequently discussed, although some studies report partial compensation of these effects [9]. Mosaic-level stripe noise, often resulting from inconsistent swath intensities across survey lines, is illustrated in Fig. 3 and has been addressed using 2D Fourier-based filtering approaches [21].

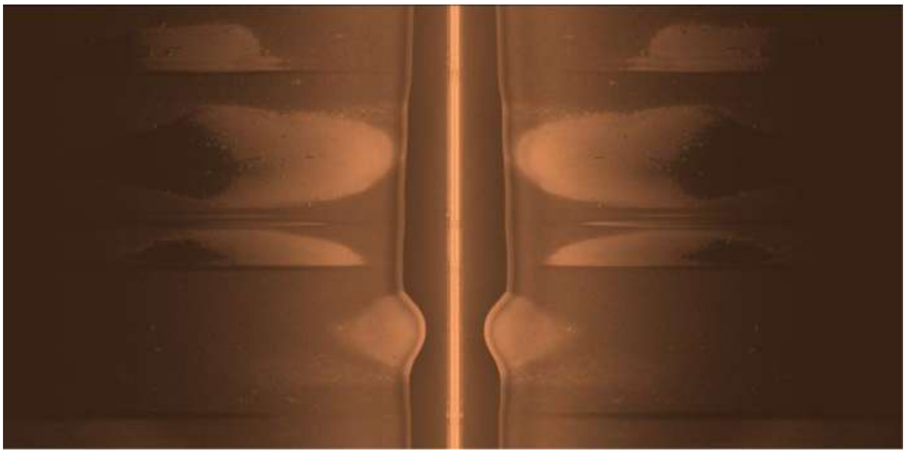

Fig. 1. An example of intensity decay with range

The intensity variations make sonograms less readable by humans and cause other hindrances in subsequent image processing and usage [22]. Ramifications include loss of information in under- or over-ensonified areas, distortion of distinctive features, poor reception by AI and post-processing software [12], failures in detection and classification [23, 14] of objects and sediment types segmentation [5], unwanted artifacts on mosaics [18, 21] and complicate fusion with other data from other modalities [16, 19, 4]. This highlights the importance of adequate intensity correction methods that correspond to sonogram use cases.

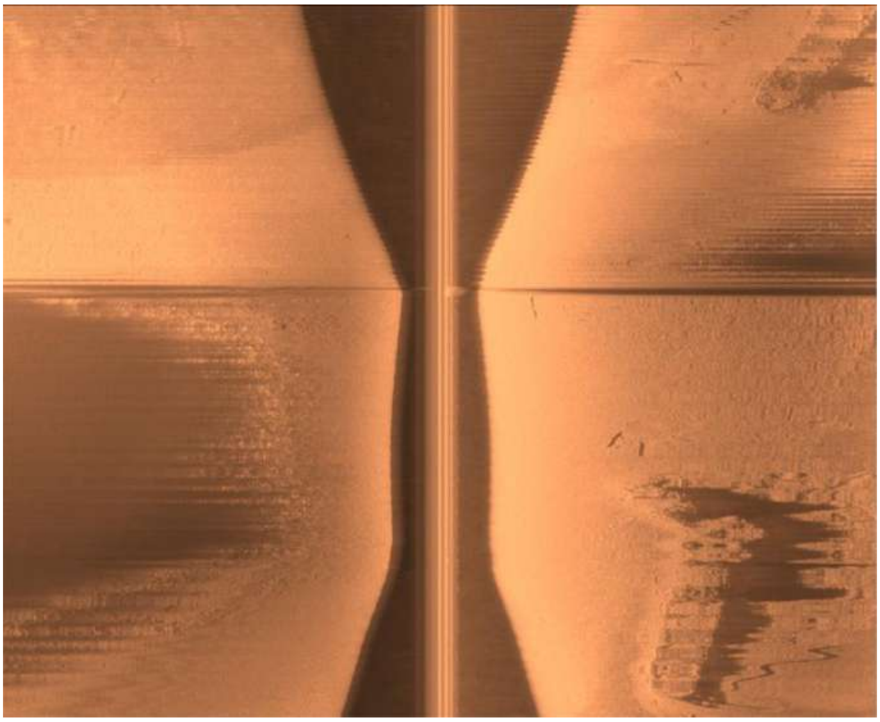

Fig. 2. An example of over-ensonified near-nadir area (bright areas in the middle) and stripe noise (frequent horizontal lines of various intensity and length)

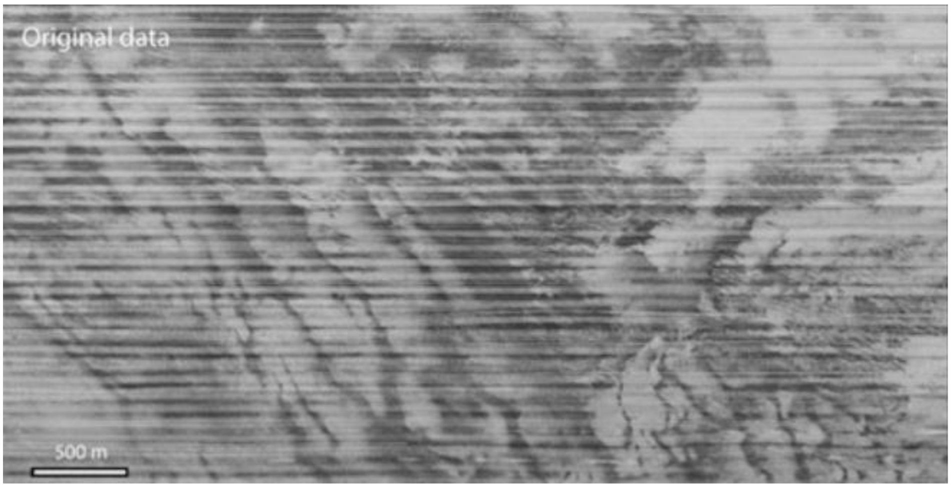

Fig. 3. An example of stripe noise on sonar mosaic caused by intensity variations [21]

Due to the variety of sonogram applications, the methods of sonar data processing also have significant diversity. A sonogram is a synthetic image without any reference to "ground truth" that can be seen and evaluated by a human eye. As formulated by Blondel in [1]: "The "quality" of an image is very subjective… Is a higher contrast necessarily better? What would be the optimal contrast?". No single method can be deemed universal or true in the application to different sonogram use cases. For example, researchers may want to mark different sediment or underwater vegetation with different shades of gray and that will significantly affect the choice of intensity correction methods. Processing legacy sonogram data is another use case that sets up requirements for processing methods.

Legacy sonograms, especially recorded on analog media, may not contain complementary information like navigational data, vehicle or towfish motions, sonar type and calibration. Thus, applicable methods should only use the data present on the sonogram itself. Some objectives may contradict others like making the image intensity more uniform for better readability and keeping variations in sediment brightness or acoustics shades for better or object detection and classification. Not every method reviewed in this research mentions the particular use case it works best for, most of them pretend to be generic. However, if particular use cases have been specified by the paper author, we will include them in the resulting table.

Various intensity correction approaches for side-scan sonar imagery are based either on physically informed models of acoustic propagation and reflection or on statistical and signal-based techniques aimed at achieving radiometric uniformity under diverse environmental and operational conditions. Ye [4] has split intensity correction methods into six categories: Time Variant Gain (TVG), Histogram Equalization (HE), Nonlinear Compensation, Function Fitting, Sonar Propagation Attenuation Model and Beam Pattern. However, some methods like [12], may be classified into two proposed categories. Our classification will be less strict but more descriptive, outlining the main model or approach of each method: regression over ping intensity profiles, averaging along or across track, Lambertian model of sound reflection, etc. Several examples of intensity correction using different methods are shown in Fig. 4 [4].

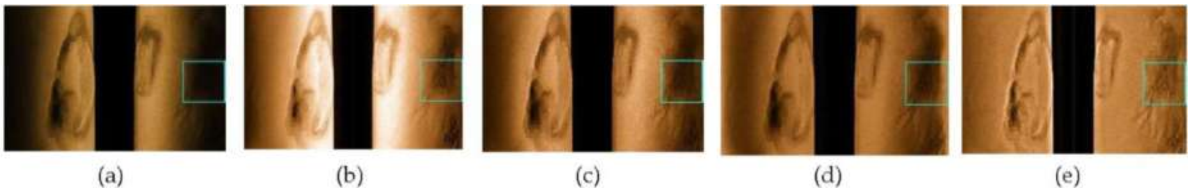

Fig. 4. Comparison of intensity correction in side scan sonar images:
a – original image; b – histogram; c – non-linear compensation; d – function fitting; e – method in [4]

In our subjective opinion, methods that do not use any model, especially those using averaging, are easier to implement using packages and modules of statistical processing. Moreover, such modules are available in abundance. On the other hand, module-based methods may produce better results in complicated circumstances.

Every model is a simplified representation of the target objects. With all the complexity of sound emission, propagation, and reflection underwater, different methods resort to different assumptions and declare various limitations in order to simplify the modeling process. Most common assumption considers the seafloor to be flat and uniform across-track at a particular point. This greatly simplifies calculation of grazing angle and other values from altitude and slant range data. Lambertian assumption (Lambertian law) [1] is another popular assumption with researchers. It states that intensity of the reflected signal is proportional to cosine of the angle between the incident light and the surface normal, which is a fairly good approximation in most cases. Other assumptions may include small variation in depth during sonar mission, uniformity of depth and sediment in some proximity of the calculation point.

Method users must be aware of such assumptions and limitations as they restrict method applicability or cause side effects when assumptions do not hold. For example, if the seafloor is not flat with high depth and slope variations, it may cause over- or undercompensation of a signal. Table 1 illustrates the main models or approaches, declared assumptions and limitations of the reviewed methods.

Sonograms may comprise hundreds of thousands of lines with thousands of data points in each line. This may result in gigabytes of information produced during relatively short exploration missions. With this regard, computational effectiveness is a very important criterion of choice when it comes to selecting a proper processing method.

Recent achievements in controlled and unmanned vehicle design pose new requirements for effectiveness of on-board signal processing units given limited onboard computational power, energy consumption, connection line bandwidth or absence of timely feedback from the operator. There may also be a need for real-time processing like instant object recognition during autonomous navigation. Some use cases that presume quick reaction time (mine detection or rescue missions to name a few) may require real-time or nearly real time performance which also limits the choice of methods.

Few works provide quantitative estimates of computational complexity, some claim effectiveness or suitability for real-time usage qualitatively. Moreover, processing time greatly depends on implementation details, optimization techniques and, of course, available hardware. This makes a direct comparison of method's speed barely possible.

However, we may assume that methods employing averaging techniques prove to be quite effective in terms of computational resources. On the other hand, effective use of along-track averaging is only possible after the whole mission or a significant part of it has been completed which prevents them from being used in real-time. One should also consider the year of publication and advance in computational power and software tools since then. Besides the intensity correction itself, some of the researched methods offer additional benefits for their users. This can be a calculated sonar beam pattern or detected sediment type. Table 2 lists the methods' computational complexity and side outputs.

A range of fundamental and supplementary techniques employed in intensity correction methods has been identified in the literature. These approaches reflect both physically grounded and data-driven strategies for improving sonar image consistency. Common techniques include intensity averaging across the track line, along-track direction, or within local pixel neighborhoods [8, 9, 13]; regression-based modeling of sonar ping data using exponential, spline, or other types of interpolation [16, 22]; and frequency-domain separation to isolate low- and high-frequency signal components. The latter can serve purposes such as decomposing illumination and reflectance [4, 9, 22] or mitigating stripe noise artifacts [21].

Table 1

Methods classification by use case, model, and basic assumptions

Reference	Use case(s) / problem	Model or Approach	Assumptions and limitations
Al-Rawi 2016 (MIRA) [10]	– Fusion – Generic	Exponential regression of a ping	Exponential distribution of signal
Al-Rawi 2017 (Cubic spline) [16]	– Mapping – Underwater computer vision	Cubic spline regression of a ping	Rayleigh distribution of signal
Anstee 2001 [18]	Mosaicking	– Along and across track averaging, separately for near nadir area and remaining area	– Flat floor – Altitude does not change much – Not been tested with data from lower frequency side scan sonars
Burguera and Oliver 2014 [12] Burguera and Oliver 2016 [23]	– Mapping – Navigation or SLAM – Mosaicing – Generic	– Lambertian model – Sensitivity pattern model by Kleeman and Kuc – Beam pattern model	– Flat floor – Lambertian assumption
Capus 2004 [19]	– Mosaicking – Classification – Conversion to 8-bit – Correction of TVG residuals and beam pattern	– TVG model – Along-track average – Beam pattern estimate	– Small altitude changes – Platform stability with respect to pitch and roll – Seafloor unchanging in slope across track
Capus 2008 [13]	– Mosaicking – Segmentation – Correction of TVG residuals	– Imaging model – Quadratic function describing the variations in intensity associated with sonar altitude – Beam pattern model – Iterative process to separate angular and range dependent intensity variations	– Suitable for shallow water and low altitude – Errors arise at each course alteration – Needs a suitable exemplar image for generation of correction factors.
Yet-Chung Chang 2010 [24]	– Mosaicking – Generic	– Average signal intensity for each grazing angle – Average energy level of the 20 pings – Normalizing ping energy levels to remove	– Total back-scattered energy from each ping should be similar to adjacent pings in the time series
Clarke 2004 [14]	– Classification	– Combining a number of discrete spatial frequency bins with average backscatter strength – Stack backscatter strength information in angular bins – Empirical approach was to estimate beam patterns	– Flat floor – Shallow water
Galdran 2017 [25]	– Mapping – Generic	– Exploiting two-dimensional information to estimate and remove intensity nonuniformity – Locally normalizing the intensity in each region to retrieve a more regular image	– Simple logarithmic dynamic range compression is applied to compress the received acoustic signal – Background intensity follows a normal distribution
Shippey 1994 [20]	– Mosaicking – Segmentation	– Histogram normalization to normal distribution – Preserve the characteristic histogram shape for each sediment	– Not ideal for the segmentation task
Wilken 2012 [21]	– Mosaicking – Stripe noise removal – Classification	– 2D Fourier transformation adjusting slope angle of the stripe noise and filtering width	– Spatial Nyquist sampling criteria must be fulfilled – Sand ripples prone to elimination by the filtering process – Data gaps / clipped areas appear smeared or blurred along all filtered stripe directions
Jianhu Zhao 2017 [5]	– Generic – Sediment variations	– Linear relationship between distortion and sonar altitude – Average angle–backscatter curves of individual sediment – Unsupervised sediment classification – Angle-related radiometric correction applied for each sediment	None
Cervenka 1993 [22]	Mosaicking	– Filter the low spatial frequency components of the image using Chebyshev polynomials – Contrast enhancement through histogram equalization by balancing local versus global histogram contribution	– The original image must fit exactly into a rectangular frame for the method to work satisfactorily

End of Table 1

Yifei Liu 2023 [8]	– Mosaicking – Classification in rugged terrain	– Multiplicative Attenuation Model – Divide the image into multiple segments along the vertical direction of the track – Image is segmented along the attenuation direction, and the segmentation intensity is calculated by using the multiplicative model for the echo points. – Maximum segmentation intensity is taken as the target intensity, and the non-shaded points of the image are compensated and corrected	– Seawater is uniform – Influence of boundary loss is not discussed
Xiufen Ye 2019 [4]	Generic	– Retinex mean filter or bilateral filter to directly smooth signal intensity – Mean filter and bilateral filter	None
Li, Shaobo 2022 [9]	Generic	– Lambert's law and the variational Retinex model – Beam pattern model – Low-rank constraint to obtain a better illumination component. – ATV constraint is used to retain geomorphology features and remove the stripe noise	– Illuminance component in log domain is smooth in spatial – Should be applied to the geometric corrected SSS image where the water column has been removed

Table 2

Classification of Methods by Computational Complexity and Side Outputs

Reference	Computational complexity / performance	Side outputs
Al-Rawi 2016 (MIRA) [10]	Within the order O(N), N = total number of pixels in the image	None
Al-Rawi 2017 (Cubic spline) [16]	n/a	– The peak of the estimated distribution is related to the sensor gain – Can also be used to detect high acoustic reflectance and acoustic shadows of underwater landmarks
Anstee 2001 [18]	"The algorithm imposes minimal processing overheads on modern personal computers." [Anstee]	n/a
Burguera and Oliver 2014 [12]	n/a	n/a
Burguera and Oliver 2016 [23]	n/a	Echo Intensity Map
Capus 2014 [19]	n/a	– Beam pattern model – TVG residual model
Capus 2008 [13]	– Typical processing times for a 2000 x 2000 pixel image, including resampling, would be between 2 and 15 s depending on altitude variation.	n/a
Yet-Chung Chang 2010 [24]	n/a	n/a
Clarke 2004 [14]	n/a	– Roll-caused stripe noise removal
Galdran 2017 [25]	"Great computational efficiency, being a good candidate for a real-time implementation." Complexity O(N), N = total number of pixels in the image	n/a
Shippey 1994 [20]	n/a	Column histogram for each sediment type
Wilken 2012 [21]	n/a	Can be applied to non-optimally processed side-scan mosaics
Jianhu Zhao 2017 [5]	n/a	Sediment classification
Cervenka 1993 [22]	"From a practical point of view, Chebyshev analysis is not difficult to perform."	n/a
Yifei Liu 2023 [8]	"Exhibits excellent performance in image correction"	n/a
Xiufen Ye 2019 [4]	– Mean filtering suitable for online processing – Bilateral filtering method is more suitable for offline processing	Can also be used to enhance low illumination color optical images
Li, Shaobo 2022 [9]	n/a	Stripe noise removal

Bottom detection based on altitude measurements or water column analysis is also widely applied [19], although it presents specific challenges in high-noise environments or areas with abrupt bathymetric variations.

Slant range correction (resampling) is often a prerequisite for precise grazing angle computation or enhanced spatial averaging [19, 24]. In some methods, sediment classification – either predefined or derived post hoc – is used to improve reflectivity estimation and aid intensity normalization [20, 5].

Other widely used techniques include histogram leveling [20, 3], outlier filtering using Z-score methods [5], and Bayesian inference of time-varying gain (TVG) profiles directly from sonar image data [17]. These tools are not only useful for intensity correction but also show potential for the development of novel methods or as auxiliary components in broader image processing pipelines. Several additional methods, while not directly designed for intensity correction, offer valuable insights into sonar image enhancement. For instance, Nguyen [26] introduced an empirical technique to estimate beam patterns, and Tamsett [27] proposed a more accurate TVG correction model by dividing the ensonified seafloor into primary and conjugate zones. He also suggested a method for deriving the sonar's beam function [15]. Calder [17] employed Bayesian inference to reconstruct the TVG profile solely from image data and applied it to mitigate residual sonar artifacts. Completely objective evaluation of intensity correction methods remains challenging due to the lack of a definitive ground truth in sonar imaging. Nevertheless, various quantitative approaches have been used for performance assessment. Comparative analysis of multiple methods, such as MIRA versus Dark Channel Prior (DCP), offers direct insights into algorithmic differences [10]. Histogram-based evaluation focuses on distribution shape, deviation from normality, balance, and the presence of distinct modes; some studies calculate the coefficient of variation (CV) as a supporting metric [16, 5]. Several standardized and purpose-built metrics have also been proposed. The Sonar Image Quality Evaluation Metric (SIQEM) [10] provides a domain-specific assessment framework. Structural Similarity Index (SSIM) is used to quantify perceptual similarity between two images [28], while peak signal-to-noise ratio (PSNR), entropy, standard deviation, and mean gradient serve as general image quality indicators [4]. Additional metrics such as the Vollrath function, Roberts function, Brenner gradient, mean gradient, and gray-level difference have been utilized for fine-grained assessments [3, 8].

These evaluation tools can support the benchmarking of new intensity correction methods or comparative studies across different imaging conditions and datasets.

Conclusion

This study addresses the issue of intensity correction in side scan sonar imagery, an essential task for accurate underwater analysis and mapping. Given the widespread use of side scan sonar in fields ranging from oceanography and archaeology to military applications, the need for effective intensity correction methods specific for particular use cases is paramount. We have identified various reasons for intensity variation in sonograms, including factors like sound attenuation, sonar beam patterns, time-varied gain (TVG) residuals, and environmental conditions. Through an extensive literature review and method analysis, we have categorized and evaluated the discovered intensity correction methods based on their models, assumptions, computational complexity, and practical applications. Our findings highlight that no single method is universally applicable due to the diversity of sonar images use cases and intensity variation reasons. While some methods excel in real-time processing scenarios, others may provide more accurate corrections using sophisticated models at the cost of computational complexity. The results prove that a variety of correction methods are available covering different variation reasons, use cases and computational requirements that provide a good selection for implementation and evaluation. We have also listed the main techniques used within the methods that can prove useful in implementation and research. Intensity correction is one of the first mandatory steps in any sonar imaging processing tasks like object detection and segmentation that will be covered in our future research.

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