The Impact of a Deep Learning Self-Adaptive Colour Restoration Pipeline for Deep Underwater Images in 3D Reconstruction

Marinos Vlachos [1], Dimitrios Skarlatos [1], Stella Demesticha [2]

[1] Cyprus University of Technology, Department of Civil Engineering and Geomatics, Photogrammetric Vision Lab
2-6 Saripolou str., 3036, Limassol, Cyprus – (marinos.vlachos, dimitrios.skarlatos)@cut.ac.cy
[2] University of Cyprus, Archaeological Research Unit, PoBox 20537, Nicosia 1678, Cyprus – demesticha.stella@ucy.ac.cy

Keywords: Colour Restoration, Underwater Photogrammetry, Feature Matching, Structure-from-Motion, 3D Point Clouds.

Abstract

Underwater photogrammetry is challenged by image degradation caused by water absorption and scattering, which negatively impacts feature detection and 3D reconstruction quality. This study aims to evaluate the effectiveness of a Feedforward Neural Network-based colour correction method designed to enhance underwater image quality, thereby improving feature matching and subsequent 3D reconstruction processes. The proposed approach leverages deep learning to correct colour distortions without relying on physical models of underwater light propagation. Evaluation was performed using established feature detection algorithms, such as SIFT and SURF, applied to multiple underwater datasets capturing diverse imaging conditions. The goal is to determine whether neural network-based colour correction can increase the number of valid feature correspondences, improve sparse and dense point cloud generation, and ultimately support more accurate and robust 3D reconstructions. By integrating this correction method within a photogrammetric workflow, the study investigates the potential benefits and limitations of data-driven colour enhancement in underwater environments. The findings are intended to inform future development of hybrid approaches that combine physical modelling with deep learning, aiming to optimize both visual clarity and geometric fidelity in underwater mapping and documentation. This work contributes to advancing underwater photogrammetry by addressing critical challenges related to image quality and reconstruction accuracy, with implications for archaeological surveys, marine research, and underwater infrastructure inspection.

1. Introduction

Underwater (UW) images often exhibit radiometric inconsistencies due to the optical properties of water. As light travels through a water body, its intensity diminishes, leading to colour degradation. This absorption intensity varies depending on wavelength, depth, the distance between the camera and the subject, and the physical and environmental conditions of the water at a specific location and time. Fields such as underwater archaeology and marine biology rely on accurately coloured images that reflect real-world objects. This need has driven research into automatic and semi-automatic colour correction techniques, which are commonly applied during the pre- or post-processing phases of photogrammetric workflows.

One major challenge in UW imaging is the unnatural blue-green tint seen in underwater photographs. This phenomenon arises from several factors unique to aquatic environments, which are not encountered in air. As light passes through water, it experiences substantial attenuation, causing its intensity to weaken exponentially with distance (Jaffe, 1990). Moreover, this attenuation depends on frequency, red light fades significantly faster than blue light, and backscattering of blue and green further alters the perceived colour of objects depending on their distance from both the camera and the light source (Bryson et al., 2016). To counteract these issues, various studies have proposed computational approaches to restore the 'true' colours in UW images (Akkaynak and Treibitz, 2019; Bryson et al., 2016).

For underwater surveys, having access to both radiometric details and high-resolution 3D data is essential for interpreting information about the surveyed environment (Menna et al., 2018). The development of fully automated photogrammetric software has significantly enhanced underwater documentation and reconstruction, leveraging Structure from Motion (SfM) and Multi-View Stereo (MVS) techniques. These innovations have contributed to advancements in disciplines such as underwater archaeology and marine biology. Modern photogrammetry allows experts to track and document changes in UW sites with high precision, ensuring continuous and up-to-date monitoring.

Our previous work introduces a Self-Adaptive Colour Restoration pipeline designed for restoring true colours in archival underwater imagery (Vlachos and Skarlatos, 2024). The methodology integrates Structure from Motion (SfM) and Multi-View Stereo (MVS) techniques to derive depth maps and sparse point clouds. A manually guided selection of well-lit "ground truth" RGB values is used to train a Feedforward Neural Network (FNN), which learns to model colour degradation as a function of Camera-to-Object Distance. Optimized using Adam optimizer, the trained network predicts and restores colour without requiring environmental or spectral data. The approach is particularly suited for datasets captured with single-camera, strobe-equipped setups, ensuring geometric consistency. By leveraging SfM for identifying reliable colour references, the pipeline effectively reverses underwater colour attenuation, enhancing image feature matching and 3D reconstruction. Results from diverse sites, including Mazotos and Nissia, demonstrate the pipeline's robustness, providing a practical solution for improving the visualization and documentation of underwater archaeological sites.

Expanding on this research, this paper will examine the effect of the Self-Adaptive Colour Restoration pipeline on feature extraction and matching processes, as well as its influence on the 3D dense point cloud reconstruction of UW environments. Specifically, it will investigate whether applying colour correction enhances the accuracy and overall quality of these subsequent stages, namely Structure from Motion and 3D reconstruction, when applied to the corrected datasets.

2. Related Work

Over the last decade, numerous techniques have been developed for both enhancing and restoring images, as well as for evaluating how such techniques influence 3D reconstruction processes. This section outlines key advancements in these areas and discusses their relevance to the current work.

2.1 Image Enhancement and Restoration

Researchers have extensively explored the optical characteristics of water, particularly its absorption and scattering behavior. Jerlov's seminal classification in 1951 identified three main oceanic and five coastal water types (Jerlov et al., 1951). Building on this foundational work, subsequent studies sought to quantify the inherent optical properties of these water categories (Akkaynak et al., 2017; Solonenko and Mobley, 2015).

Unlike conventional RGB-based colour correction methods, a model introduced in 2014 approached the problem through spectral analysis of aquatic optical properties (Blasinski et al., 2014). Another model (Akkaynak et al., 2017) relied on real-world aquatic data to categorize natural waters and pinpoint the RGB attenuation coefficients crucial for underwater (UW) imaging. This study revealed that oceanic wideband attenuation coefficients are relatively constrained and illustrated the complexity involved in transitioning from wavelength-specific attenuation $\beta(\lambda)$ to broadband attenuation $\beta(c)$, thereby challenging simplified image formation models.

An early method for correcting colours in UW images using the $l\alpha\beta$ colour space was detailed in (Bianco et al., 2015). This approach involved white balancing the chromatic elements and applying histogram-based luminance adjustments to improve contrast. The methodology performed effectively under certain assumptions, such as uniform scene illumination and the "grey world" condition, which generally hold in close-range, downward-viewing scenarios like seabed imaging or underwater photography under stable lighting.

The work in (Bryson et al., 2013) introduced an automated correction approach for UW image colour inconsistencies captured from varied perspectives during 3D structure-from-motion reconstructions. The aim was to document extensive marine ecosystems without disrupting them with colour charts. This was achieved through a colour constancy strategy based on a grey-world distribution, assuming scene geometry does not affect surface reflectance. Later, the same authors presented a novel image formation model designed specifically for a setup involving strobes and an autonomous UW vehicle (Bryson et al., 2016). This allowed for accurate colour recovery tailored to the equipment configuration.

Expanding on these efforts, the researchers in (Akkaynak and Treibitz, 2018) refined the UW image formation model by integrating empirical oceanographic data to more accurately represent the backscatter component. Their findings highlighted a discrepancy between the wideband coefficients of backscatter and those of direct transmission, contrary to prior assumptions. Consequently, they proposed a new model that accounted for this distinction and validated it through in situ testing. This updated model was later operationalized in (Akkaynak and Treibitz, 2019) through the Sea-thru pipeline, which, while offering enhanced physical accuracy, introduced additional parameters that added complexity to its practical use.

2.2 Influence on Underwater Photogrammetry and 3D Reconstruction

In (Li et al., 2018), the researchers designed a multiterm loss function combining adversarial loss, cycle-consistency loss, and the Structural Similarity Index Measure (SSIM). Drawing inspiration from CycleGANs, they proposed a weakly supervised framework for UW image colour correction, aiming to simulate how the scene would appear outside of water. Their results not only enhanced visual quality but also improved image feature matching performance.

A different strategy introduced in (Ancuti et al., 2012) involved a fusion-based enhancement method that utilized a single input image, integrating several popular filtering techniques. This approach was particularly effective in scenarios with dynamic underwater environments and significantly enhanced feature detection and matching capabilities.

In another study (Mangeruga et al., 2018), five leading image enhancement techniques were applied to datasets collected from various underwater locations with differing depths, turbidity levels, and lighting conditions. The enhanced images were assessed using three evaluation strategies, one of which focused on their effect on dense 3D point cloud reconstruction outcomes.

3. Materials and Methods

The primary datasets for this research were obtained from the Mazotos shipwreck, a 4th-century BC merchant vessel situated approximately 45 meters underwater off the southern coast of Cyprus (Demesticha, 2011; Demesticha et al., 2014). Data acquisition was conducted during three distinct excavation campaigns, each utilizing different camera systems to assess the method's resilience to variations in environmental conditions and equipment. Specifically, images were collected using a Canon EOS 7D in 2018 and a Sony SLT-A57 in 2019, both outfitted with underwater housings and strobes to ensure quality imaging.

Further data collection occurred in September 2024, during a field campaign organized by the Maritime Archaeological Research Laboratory (MARELab) at the University of Cyprus, contributing to the robustness of the evaluation framework.

To examine the adaptability of the proposed methodology in a different underwater setting, an additional dataset was gathered in 2024 at a second archaeological site; an 18th-century shipwreck located near Nissia tou Protara in Famagusta Bay, Cyprus, resting at a depth of 28 meters. Known to divers since the 1980s and formally reported to the Department of Antiquities in 1992 ("Nissia Shipwreck - Multimedia Applications for Cypriot Maritime Cultural Heritage," n.d.), the site has suffered from unregulated visits and looting. Systematic archaeological exploration began in 2014 under the direction of MARELab, supported by the Honor Frost Foundation, and has since included two major excavation campaigns: the first in 2017, which also hosted a field school in collaboration with the Nautical Archaeological Society, and the second in 2024, partially funded by the THETIDA project.

A Nikon D610 camera was employed for image capture during the 2024 campaign. These excavation seasons revealed significant portions of the vessel's wooden hull, along with cannons and various onboard artifacts. Throughout all phases of work at the site, photogrammetric documentation has been integral; not only for detailed recording of archaeological material but also for site monitoring and the formulation of conservation strategies.

Figures 1-3 showcase the original vs colour corrected images that resulted after the implementation of the Self-Adaptive Colour Calibration Pipeline.

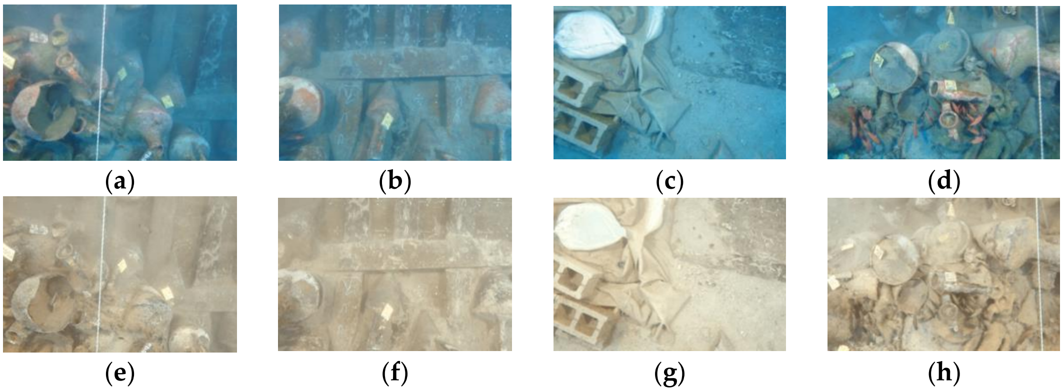

Figure 1: Training results on 4 images with Adam and RMSprop optimizers ((a–d) Original images, (e–h) Adam optimizer-based prediction results). Dataset A, Camera: Sony SLT-A57. Images acquired at the Mazotos shipwreck site. Credits: MARELab, © University of Cyprus. Photographer: Massimiliano Secci.

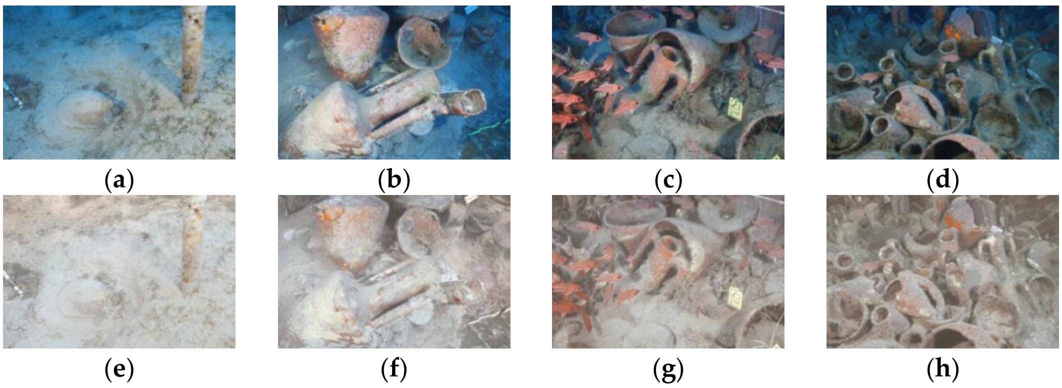

Figure 2: Training results on 4 images with Adam and RMSprop optimizers ((a–d) Original images, (e–h) Adam optimizer-based prediction results). Dataset b, Camera: Canon EOS 7D. Images acquired at the Mazotos shipwreck site. Credits: MARELab, © University of Cyprus. Photographer: Andreas C. Kritiotis.

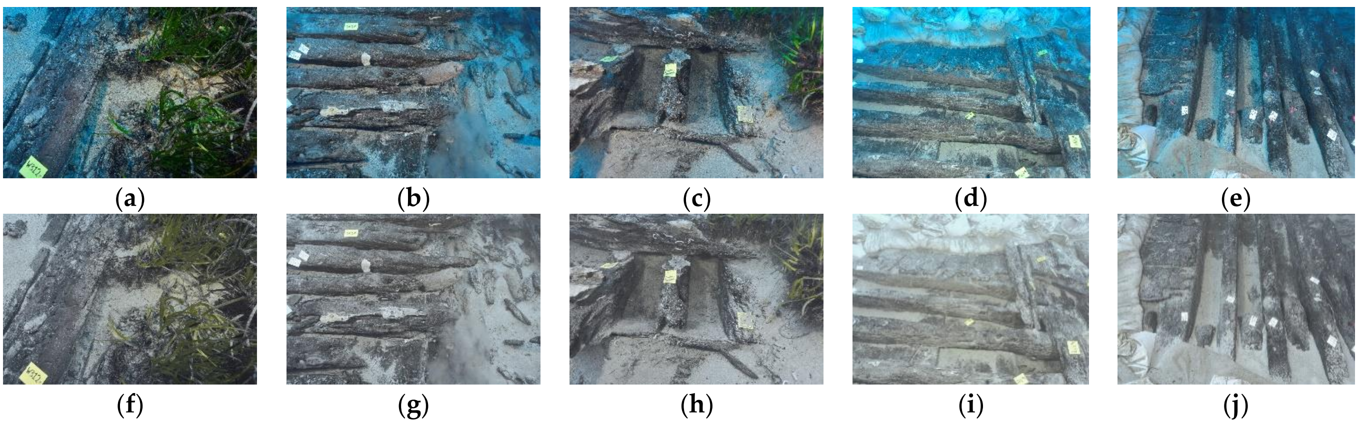

Figure 3: Training results on 5 images with Adam and RMSprop optimizers ((a–e) Original images, (f–j) Adam optimizer-based prediction results). Camera: Nikon D610. Images acquired at the Nissia shipwreck site. Credits: MARELab, © University of Cyprus. Photographer: Andonis Neophytou.

https://doi.org/10.5194/isprs-archives-XLVIII-2-W10-2025-309-2025 |

3.1 Network Architecture for Colour Restoration

A Feedforward Neural Network (FNN) was chosen for its simplicity, computational efficiency, and ability to model both linear and non-linear relationships which is ideal for this relatively straightforward task (Aggarwal, n.d.; Géron, n.d.; Goodfellow et al., 2016; Müller and Guido, n.d.). Its straightforward design allows quick experimentation with different architectures and hyperparameters, balancing accuracy with resource use.

The model was implemented in MATLAB, using a structured workflow: data were split into training (70%), validation (15%), and testing (15%) sets. Training used (Xtrain, Ytrain), validation with (Xval, Yval) helped tune parameters, and (Xtest, Ytest) was used for final evaluation.

The network comprised an input layer with four neurons (R, G, B, CoD), two hidden layers with ten ReLU-activated neurons each, and an output layer predicting Rtrue, Gtrue, and Btrue values. This setup was designed to optimize performance with minimal computational overhead (Figure 4).

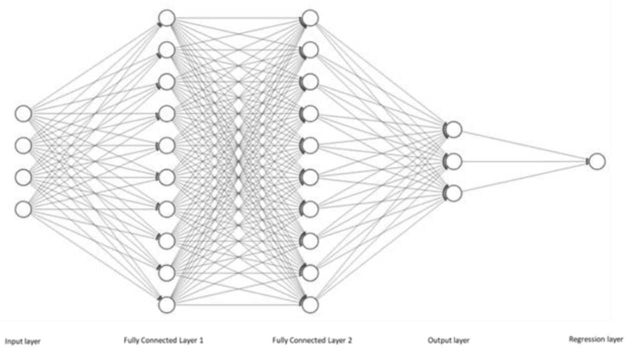

Figure 4: Network architecture of FNN used for training.

3.2 Dense Point Cloud generation and Image Feature matching

After restoring the colours of the scene for both sites, a 3D reconstruction using the corrected images will be done in order to compare the performance of the colour corrected datasets versus the originals in regard to dense point cloud generation. Additionally, a comparison regarding the performance of image feature matching and SfM point extraction on the colour corrected images was done.

3.2.1 Image Feature Matching & SfM Evaluation

The algorithm's initial evaluation focused on its ability to enhance image feature matching, an essential step in photogrammetry and 3D reconstruction. SIFT and SURF algorithms were applied to nine image pairs (three from each site: Mazotos and Nissia) to test performance under varying underwater conditions.

The goal was to assess whether colour correction improved the number of valid feature correspondences. Both algorithms were tested with a 95% confidence level and a 0.5-pixel distance threshold. RANSAC was used to eliminate false matches and retain geometrically consistent pairs.

The image feature matching experiment was conducted in MATLAB using its computer vision toolbox. The number of valid matches before and after colour correction was compared, with results, summarized in Table 1, demonstrating clear improvements in matching accuracy and density.

An additional experiment was conducted to assess the impact of colour correction on the number of Structure-from-Motion (SfM) points generated in the sparse point cloud. The SfM reconstruction was performed using Agisoft Metashape v2.0.2, with the processing accuracy set to high. To ensure data quality, only points matched in at least three images were retained; points observed in just two images were excluded from the analysis. Table 2 presents the total number of valid sparse points for both the original and colour-corrected datasets.

Image Pairs	SURF			SIFT		
	# of valid matches original	*# of valid matches colour corrected*	*% improvement*	*# of valid matches original*	*# of valid matches colour corrected*	*% improvement*
P_A1	15	17	13%	430	467	9%
P_A2	224	277	24%	1957	2086	7%
P_A3	54	47	-13%	150	134	-11%
P_B1	91	97	7%	673	754	12%
P_B2	128	140	9%	766	966	26%
P_B3	719	746	4%	324	378	17%
P_C1	11697	13008	11%	18025	20350	13%
P_C2	1426	1512	6%	4493	5262	17%
P_C3	8321	8196	-2%	15197	13602	-10%

Table 1: Statistics of SIFT & SURF image feature matching when applied on the original & colour corrected image pairs.

Dense Cloud		***# of SfM points***	***% gain / loss***
Dataset A (Mazotos 2018)	***Original***	61002	8%
	Adam CC	66167	
Dataset B (Mazotos 2019)	***Original***	138337	-9%
	Adam CC	125712	
Dataset C (Nissia 2024)	***Original***	467326	-5%
	Adam CC	443836	

Table 2: Number of total SfM points on the Original and Colour-Corrected Datasets.

The evaluation results, presented in Table 1, demonstrate the impact of the proposed colour correction algorithm on the performance of image feature matching using the SIFT and SURF descriptors. Overall, the application of the correction method led to an increased number of valid feature correspondences in the majority of the tested image pairs, confirming its effectiveness in enhancing image quality under underwater conditions.

For the SURF algorithm, an improvement in feature matching was observed in 7 out of the 9 evaluated image pairs. The most substantial enhancement occurred in image pair P_A2, which exhibited a 24% increase in valid matches following colour correction. Similarly, SIFT demonstrated improvements in 7 out of 9 pairs, with the highest gain recorded in P_B2, where the number of valid correspondences increased by 26%. These results suggest that the proposed correction method is particularly effective in improving image distinctiveness in scenarios where original underwater imagery may suffer from poor colour contrast or attenuation.

Notably, a few image pairs showed a decline in performance after colour correction. In particular, both SURF and SIFT produced fewer valid matches for P_A3 and P_C3, with reductions as high as 13% and 11%, respectively. This indicates that in some cases, the correction process may inadvertently suppress critical image features or introduce visual artifacts that hinder effective descriptor matching. These exceptions highlight the importance of developing adaptive or context-aware correction strategies to ensure consistent performance across varying underwater scenes.

Despite these isolated cases of performance decline, the results consistently indicate that SIFT benefits more from the colour correction process compared to SURF, likely due to its higher sensitivity to improvements in image gradient and contrast. Overall, the proposed method contributes to more accurate and robust feature matching, supporting its integration into underwater photogrammetry and 3D reconstruction workflows.

The impact of the proposed colour correction on the Structure-from-Motion (SfM) sparse point clouds, summarized in Table 2, reflects trends consistent with the feature matching results obtained using SIFT and SURF. For Dataset A, corresponding to Mazotos 2018, the colour correction yielded an 8% increase in the number of valid SfM points, aligning well with the improvements observed in feature correspondence counts for this dataset. This suggests that enhanced feature matching quality directly contributes to denser and more reliable 3D reconstructions.

Conversely, Datasets B and C showed a decrease in SfM points (-9% and -5%, respectively), paralleling the smaller or negative gains observed in feature matching for some image pairs. This outcome highlights that while colour correction generally improves feature detection, its benefits on 3D reconstruction density can vary depending on dataset-specific imaging conditions. Overall, the SfM results do not fully corroborate the notion that improved feature matching, particularly under challenging underwater conditions, tends to facilitate denser sparse reconstructions, but adaptive correction strategies may be required to maximize gains across diverse scenarios.

3.2.2 Dense Cloud Evaluation

To enable a meaningful comparison between dense point clouds, one dataset must serve as a reference. In this study, the original (uncorrected) dataset was designated as the baseline for evaluating the colour-corrected point clouds. For each test site, photogrammetric processing was carried out using Agisoft Metashape, and the block orientation along with the camera calibration parameters from the original dataset were applied to the colour-corrected images. This approach ensured that any differences in the resulting dense clouds were due solely to colour correction and not variations in alignment or calibration.

To ensure accurate scaling of the 3D models, an underwater control point network was used to provide spatial reference during dense cloud generation. The resulting point clouds were then compared using CloudCompare, an open-source software tool designed for 3D point cloud analysis.

The comparison process followed a methodology similar to that described in (Mangeruga et al., 2018; Vlachos et al., 2022). Three primary metrics were used to assess differences between the original and colour-corrected point clouds, with results summarized in Table 3 and illustrated in Figure 5:

- Total Number of Points – A direct measure of the density and completeness of each point cloud.
- Cloud-to-Cloud Distance (C2C) – Calculated as the nearest-neighbour Euclidean distance between corresponding points in the two clouds, with the average distance μ computed as:
-

$$\mu = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} x_i \qquad (1)$$

  Where x_i is the distance for each matched point and N is the total number of points.
- Surface Density – This metric reflects the local point distribution over a unit area. For each point, the number of neighbours N within a search radius r is counted, and the surface density is given by:
-

$$Surface\ Density = \frac{N}{\pi r^2} \qquad (2)$$

  This measure helps assess the structural integrity of the reconstructed surface, excluding noise from sparse or isolated points.
- Roughness – Roughness quantifies local surface irregularities by measuring the deviation of each point from a best-fitting plane computed from its neighbours. Lower roughness values indicate a smoother, less noisy surface and thus better reconstruction quality.

By applying these metrics, we assessed the impact of colour correction on the geometric accuracy and surface quality of the 3D reconstructions. The use of consistent alignment parameters, objective comparison metrics, and a scaled control network ensured that the evaluation was both robust and reliable.

Dense Cloud		Mean C2C Abs Dist. (m)	Mean Roughness (m)	Mean Density	# of MVS Points
Dataset A (Mazotos 2018)	*Original (A)*	----	0.000121	5736188	42677999
	Adam CC (A)	0.001390	0.000132	5384499	36328178
Dataset B (Mazotos 2019)	*Original (B)*	----	0.000120	2339774	57158391
	Adam CC (B)	0.001860	0.000131	2230842	48549936
Dataset C (Nissia 2024)	*Original (C)*	----	0.000100	1972502	71313201
	Adam CC (C)	0.000544	0.000109	2000424	69405235

Table 3: Metrics of Comparisons between the Original and Colour-Corrected 3D dense PCs of the three sites.

https://doi.org/10.5194/isprs-archives-XLVIII-2-W10-2025-309-2025

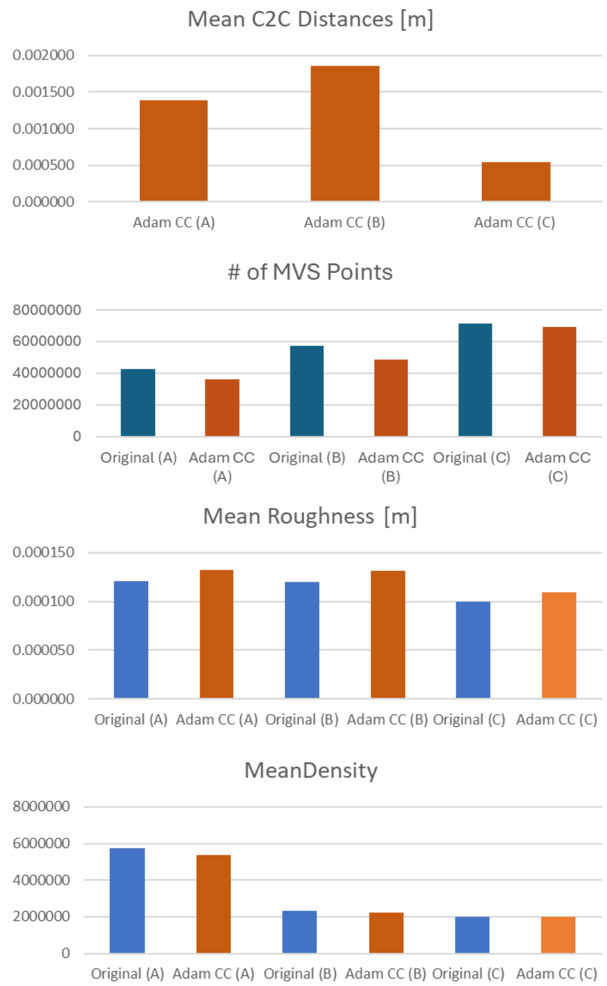

Figure 5: Visual representation of number of points, mean C2C absolute distances, roughness and surface density.

The evaluation of dense point clouds (Table 3) revealed a nuanced impact of the colour correction method on 3D reconstruction quality. In Dataset A, where feature matching and sparse SfM results showed positive gains, the dense cloud from colour-corrected images maintained a comparable roughness (0.000132 m vs. 0.000121 m) but exhibited a reduction in both surface density and total MVS points (−6.1% and −14.9%, respectively). Similarly, Dataset B showed a decline in point density and MVS points following colour correction (−4.6% and −15.1%, respectively), consistent with its earlier drop in feature match performance. Interestingly, Dataset C showed a small increase in mean density despite a modest reduction in MVS points (−2.7%), along with the lowest mean C2C distance (0.000544 m), suggesting minimal geometric deviation from the original model.

Overall, these results suggest that while the proposed colour correction method can support improved feature matching, its impact on dense cloud generation is irregular and depends on image content and environmental conditions. Small increases in roughness across all datasets (on the order of ~0.00001 m) indicate a slight increase in local surface noise post-correction. These findings highlight the importance of tuning colour correction techniques to preserve radiometric consistency while enhancing feature distinctiveness, especially in workflows where dense reconstruction accuracy is critical.

4. Conclusions

This study set out to assess the impact of a Self-Adaptive Colour Calibration pipeline implemented using a Feedforward Neural Network on the quality of underwater photogrammetric reconstructions. The central hypothesis was that enhancing image colour fidelity would lead to improved feature matching, increased sparse and dense point counts, and smoother, more complete 3D reconstructions. While the colour correction yielded notable improvements in feature detection, particularly for SIFT-based matching, the expected gains in sparse and dense point cloud generation were not consistently realized. In some cases, the corrected datasets produced fewer SfM points, reduced dense cloud density, and slightly higher surface roughness, suggesting that improved radiometric quality does not always translate into improved geometric reconstruction. These findings are in consistence with other studies on the subject, where significant geometric improvement cannot be documented when using colour enhancement or restoration techniques. This might be contributed to the fact that the originally recorded information from the camera, cannot be computationally improved in a meaningful way for geometric reconstruction.

These outcomes contrast with previous experiments where physically based correction models, grounded in underwater imaging physics, produced more consistent improvements throughout the photogrammetric workflow. The difference lies in how each method treats the image data. Physics-based approaches preserve the light propagation characteristics critical to depth estimation, while the neural network focuses on perceptual enhancement, potentially introducing inconsistencies in image gradients or local texture, which are essential for dense stereo matching.

Nevertheless, it is important to emphasize the definite visual improvement achieved by the neural network-based correction. The enhanced colour balance, contrast, and clarity significantly increase human interpretability and make critical visual features, such as object boundaries, textures, and materials, more discernible. This holds particular value for environmental studies, marine biology and underwater archaeological documentation, interpretation, and public dissemination, cases where visual clarity often takes precedence. Even when geometric benefits are limited, the improved image quality can enhance the accuracy of manual annotations, aid expert analysis, and support educational and outreach objectives.

Ultimately, these findings highlight the trade-offs between perceptual enhancement and photogrammetric precision. They also point toward the potential of hybrid models that combine the physical consistency of model-based corrections with the adaptability of neural networks. By doing so, future work may achieve both visually compelling and geometrically reliable reconstructions, which is an essential goal for high-quality underwater mapping and documentation.

Acknowledgements

The authors would like to acknowledge the photographers, Massimiliano Secci, Andreas Kritiotis and Andonis Neophytou for the image acquisition of the three datasets used for the purposes of this study.

References

Aggarwal, C.C., n.d. A Textbook Second Edition Neural Networks and Deep Learning.

Akkaynak, D., Treibitz, T., 2019. Sea-THRU: A method for removing water from underwater images. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2019-June, 1682–1691. https://doi.org/10.1109/CVPR.2019.00178

Akkaynak, D., Treibitz, T., 2018. A Revised Underwater Image Formation Model. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 6723–6732. https://doi.org/10.1109/CVPR.2018.00703

Akkaynak, D., Treibitz, T., Shlesinger, T., Tamir, R., Loya, Y., Iluz, D., 2017. What is the space of attenuation coefficients in underwater computer vision? Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017 2017-Janua, 568–577. https://doi.org/10.1109/CVPR.2017.68

Ancuti, C., Ancuti, C.O., Haber, T., Bekaert, P., 2012. Enhancing underwater images and videos by fusion. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 81–88. https://doi.org/10.1109/CVPR.2012.6247661

Bianco, G., Muzzupappa, M., Bruno, F., Garcia, R., Neumann, L., 2015. A new color correction method for underwater imaging. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives 40, 25–32. https://doi.org/10.5194/isprsarchives-XL-5-W5-25-2015

Blasinski, H., Breneman IV, J., Farrell, J., 2014. A MODEL FOR ESTIMATING SPECTRAL PROPERTIES OF WATER FROM RGB IMAGES. International Conference on Image Processing(ICIP) 610–614.

Bryson, M., Johnson-Roberson, M., Pizarro, O., Williams, S.B., 2016. True Color Correction of Autonomous Underwater Vehicle Imagery. J Field Robot 33, 853–874. https://doi.org/10.1002/rob

Bryson, M., Johnson-Roberson, M., Pizarro, O., Williams, S.B., 2013. Colour-consistent structure-from-motion models using underwater imagery. Robotics: Science and Systems 8, 33–40. https://doi.org/10.7551/mitpress/9816.003.0010

Demesticha, S., 2011. The 4th-Century-BC Mazotos Shipwreck, Cyprus: A preliminary report. International Journal of Nautical Archaeology 40, 39–59. https://doi.org/10.1111/j.1095-9270.2010.00269.x

Demesticha, S., Skarlatos, D., Neophytou, A., 2014. The 4th-century B.C. shipwreck at Mazotos, Cyprus: New techniques and methodologies in the 3D mapping of shipwreck excavations. J Field Archaeol 39, 134–150. https://doi.org/10.1179/0093469014Z.00000000077

Géron, A., n.d. Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow Concepts, Tools, and Techniques to Build Intelligent Systems SECOND EDITION.

Goodfellow, I., Bengio, Y., Courville, A., 2016. Deep Learning. MIT Press.

Jaffe, J.S., 1990. Computer modeling and the design of optimal underwater imaging systems. IEEE Journal of Oceanic Engineering 15, 101–111. https://doi.org/10.1109/48.50695

Jerlov, N.G., Koczy, F.F., (Schooner), A., 1951. Photographic Measurements of Daylight in Deep Water, Reports of the Swedish Deep-Sea Expedition, 1947-1948 ; v. 3: Physics and chemistry. Elanders boktr.

Li, C., Guo, J., Guo, C., 2018. Emerging from Water: Underwater Image Color Correction Based on Weakly Supervised Color Transfer. IEEE Signal Process Lett 25, 323–327. https://doi.org/10.1109/LSP.2018.2792050

Mangeruga, M., Bruno, F., Cozza, M., Agrafiotis, P., Skarlatos, D., 2018. Guidelines for Underwater Image Enhancement Based on Benchmarking of Different Methods. Remote Sens (Basel) 10, 1652. https://doi.org/10.3390/rs10101652

Menna, F., Agrafiotis, P., Georgopoulos, A., 2018. State of the art and applications in archaeological underwater 3D recording and mapping. J Cult Herit 33, 231–248. https://doi.org/10.1016/j.culher.2018.02.017

Müller, A.C., Guido, S., n.d. Introduction to Machine Learning with Python A GUIDE FOR DATA SCIENTISTS Introduction to Machine Learning with Python.

Nissia Shipwreck - Multimedia Applications for Cypriot Maritime Cultural Heritage [WWW Document], n.d. URL https://www.ucy.ac.cy/marecyprium/case-studies/nissia-shipwreck/ (accessed 11.14.24).

Solonenko, M.G., Mobley, C.D., 2015. Inherent optical properties of Jerlov water types. Appl Opt 54, 5392. https://doi.org/10.1364/ao.54.005392

Vlachos, M., Skarlatos, D., 2024. Self-Adaptive Colour Calibration of Deep Underwater Images Using FNN and SfM-MVS-Generated Depth Maps. Remote Sens (Basel) 16. https://doi.org/10.3390/rs16071279

Vlachos, M., Skarlatos, D., Calantropio, A., Chiabrando, F., 2022. An adhoc UW image colour correction method and the impact on image feature matching & SfM-MVS 3D reconstruction, in: 2022 International Conference on Interactive Media, Smart Systems and Emerging Technologies, IMET 2022 - Proceedings. Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/IMET54801.2022.9929653