~~w~~The best of two worlds: reprojecting 2D image annotations onto 3D models

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Abstract

Imagery has become one of the main data ~~source~~sources for investigating seascape spatial patterns. This is particularly true in deep-sea environments, which are only accessible with underwater vehicles. On the one hand, using collaborative web-based tools and machine learning algorithms, biological and geological features can now be massively annotated on 2D images with the support of experts. On the other hand, geomorphometrics such as slope or rugosity derived from 3D models built with structure from motion (sfm) methodology can then be used to answer spatial distribution questions. However, precise georeferencing of 2D annotations on 3D models has proven challenging ~~from~~for deep-sea images, due to a large mismatch between ~~the raw~~ navigation ~~inherited~~obtained from underwater vehicles and the reprojected navigation ~~inherited from bundle adjustment.~~computed in the process of ~~3D~~ building 3D models. In addition, although 3D models can be directly annotated, the process becomes challenging due to the low resolution of textures and the large size of the models. In this article, we propose a ~~new~~streamlined, open-access processing pipeline to reproject 2D image annotations onto 3D models using ray tracing. Using four underwater image ~~datasets~~data sets, we ~~evaluated~~assessed the accuracy of annotation reprojection on 3D models and ~~compared it to annotation geolocation available from the raw navigation. Features were georeferenced~~achieved successful georeferencing to centimetric accuracy~~, a 100-fold improvement over geolocation.~~. The combination of photogrammetric 3D models and accurate ~~3D~~2D annotations would allow the construction of a 3D representation of the landscape and could provide new insights into understanding species microdistribution and biotic interactions.

Introduction

~~The development of r~~Remote cameras, towed by research vessels or mounted on underwater

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platforms, ~~was used early on~~have been used for decades for underwater exploration especially in the deep sea (e.g. Lonsdale, 1977). Compared to physical sampling of the fauna, imaging is non-intrusive and non-destructive, and allows direct observation of the seabed over continuous areas (Tunnicliffe, 1990 ; Beisiegel et al., 2017). As a result, imaging has become a primary source of data to investigate interactions between seabed geomorphology and benthic megafaunal communities across spatial scales (i.e. 10s of m to kms). The method is particularly relevant for poorly accessible and/or vulnerable deep-sea ecosystems such as hydrothermal vents, cold seeps, canyons or coral reefs (e.g. Marcon et al., 2014; van den Beld, 2017; Robert et al., 2017; Girard et al., 2020). Typical ecological investigations make use of geological and biological annotations from images (Matabos et al., 2017; Schoening et al., 2017). This annotation task is complicated by the fact that, in most cases, fauna cannot be identified down to the species level, making it susceptible to annotator bias (Durden et al., 2016). The recent development of image-based catalogues of fauna and seascape features (e.g. Althaus et al., 2015; Howell et al., 2019) and the integration of these typologies into web-based annotation tools for 2D images has been widely used to mitigate identification bias by standardizing and remotely reviewing the categorization of large annotation sets (e.g., Langenkämper et al., 2017).

For spatial investigation, image-based data needs to be located in a georeferenced system. In the deep sea, the location of the image is given by the navigation data of the submarine platform (i.e. AUV, ROV or towed camera)~~. This navigation is determined~~, which are provided relative to the position of the accompanying ship on the surface by a combination of dead reckoning and acoustic navigation. The vehicle's position is calculated from its speed, heading and attitude usually provided by an Inertial Navigation System (INS) aided with a Doppler Velocity Log (DVL). To compensate for the drift of the inertial system and to provide a more accurate hybrid navigation, the dead reckoning navigation is periodically reset with the ship's position using an acoustic signal, typically the Ultra Short Baseline system (USBL) (Kwasnitschka et al., 2013). While the ship gets its position from global navigation satellite systems with metric accuracy, USBL accuracy decreases with depth and distance. Depending on the system used and its calibration, the accuracy can range from 1% to 0.1% of the slant distance. At 1000 m depth, the position accuracy is in the order of 10 m. ~~. Depending on the system used and its calibration, the accuracy may range from 1% to 0.1% of the slant distance.~~ The accuracy of image positioning may further be compromised by the horizontal distance between the transponder and the camera as well as the horizontal distance between the camera and the scene, if those factors are not taken into consideration. The accumulation of inaccuracies in ship positioning, submarine platform positioning and scene positioning means that image-based data are ~~theoretically~~seemingly inadequate to resolve abiotic and biotic processes operating at spatial scales lower than meters to decameters.

~~Recent advances in computer vision can provide access to an optimal repositioning (i.e. precision < 1 m) of underwater vehicles based on sequences of overlapping images.~~ ~~For instance~~However, using recent advances in computer vision photogrammetry, overlapping images can be

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~~reassembled~~ tightly aligned using a feature-matching algorithm while also refining *a posteriori* the position of the underwater camera. ~~As a result,~~This allows the reconstruction of underwater scenes in three dimensions (i.e., including overhang and cavities), advancing seascape ecology from 2.5D to 3D (Kwasnitschka et al., 2013; Lepczyk et al., 2021).Furthermore, the relative positioning of features over the resulting 3D model of the seabed can be as precise as 1 cm or even less (Palmer et al., 2015; Istenič et al., 2019). It should be noted however that while positions within a 3D model are internally consistent, the positioning of the 3D model itself still suffers from the inaccuracies of the navigation. But a 3D model also provides a digital terrain model (DTM) of a centimetric to millimetric precision, enabling a high-resolution mapping of the seabed bathymetry from which geomorphometric descriptors, such as slope and rugosity, can be rapidly and quantitatively derived (Wilson et al., 2007; Gerdes et al., 2019). Those terrain metrics are especially of importance when considering them as driving ecological variables (Robert et al., 2017; Price et al., 2019). ~~In addition, with the development of computer vision and photogrammetry, an overlapping image set allows reconstruction of underwater scenes in three dimensions (i.e., including overhang and cavities), advancing seascape ecology from 2.5D to 3D (Kwasnitschka et al., 2013; Lepczyk et al., 2021).~~

A remaining problem, h~~H~~owever, is that the georeferencing ~~system~~ of the 3D model~~s~~ conflicts with the acoustic-based relocation of annotations made on the 2D images, hence producing two spatially ~~incompatible~~misaligned data sets. A possible solution to cope with the mismatch between an acoustic-based positioning obtained from vehicle navigation and an optical-based positioning obtained from photogrammetry would still be to annotate the 3D model or the derived orthomosaics, instead of raw images. Some freely available software such as Potree (Schütz, 2015), 3DMetrics (Arnaubec et al., 2023) or commercial software such as VRGS (Hodgetts et al., 2015) or Agisoft Metashape (AgiSoft, 2016) already allow the direct annotation of 3D models. However, due to the additional reprojection step involved in their calculation, 3D textured models and associated orthomosaics typically have a slightly lower resolution than the raw 2D images, thus reducing the detectability of small organisms, and possibly, biasing the observed community composition (Thornton et al., 2016). While going back to the original image to identify the organism and then adding the annotation back to the 3D model is possible, this can take a significant amount of time. Annotations of 3D models can also be challenging due to the difficulty of displaying large high-resolution models and because of the longer duration required for drawing 3D geometries compared to 2D annotations. As a result, photogrammetry investigation typically focused on a subset of easily discernible organisms (e.g., Thornton et al., 2016) or on areas of a few 10s of m2 (e.g., Lim et al., 2020; Mitchell & Harris, 2020). Moreover, even if several 2D image annotation platforms exist (Biigle: Langenkämper et al., 2017, Squidle +: Bewley et al., 2015, VARS: Schlining & Stout, 2006), equivalent collaborative software for 3D annotations are yet to emerge.

Because we identified the lack of open-access and open-source methods to mutualize the benefits of 2D image annotation on web-based annotation tools and photogrammetric outcomes (i.e. internally accurate navigation and objective terrain descriptors), we propose an innovative

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workflow to ~~transform~~ project 2D annotations ~~in~~onto a georeferrenced3D ~~georeferencing system~~model (Marcillat et al., 2023). This involves the development of a function that allows re-projection of annotations made in the open-access web-based image annotation tool Biigle (Langenkämper et al., 2017) onto 3D models produced with the freely available photogrammetry software Matisse3D (Arnaubec et al., 2023). ~~If such a~~ A similar process had already been implemented in the commercial software Agisoft Metashape (Pasumansky, 2020), but our implementation is fully open-source and the entire workflow relies on open-access software. Here we explain the workflow and assess its accuracy~~The precision of the method has been assessed~~ in different deep seascapes, with two different submarine vehicles.

~~The development of remote cameras, towed by research vessels or mounted on underwater platforms, was used early on for underwater exploration especially in the deep sea (e.g. Lonsdale et al. 1977). Compared to physical sampling of the fauna, imaging is non-intrusive and non-destructive, while allowing direct observation of the seabed over continuous areas (Tunnicliffe, 1990; Beisiegel et al., 2017). As a result, imaging has become a primary source of data to investigate scales of spatial patterns (i.e. 10s of m to kms) of seabed geomorphology and benthic megafaunal communities, especially those poorly accessible and/or vulnerable (e.g. Girard et al., 2020; Marcon et al., 2014; Robert et al., 2017; van den Beld et al., 2017). Typical ecological investigations make use of geological and biological annotations made in images (Matabos et al., 2017; Schoening et al., 2017). This annotation task is complicated by the fact that, in most cases, the fauna cannot be identified down to the species level, making it susceptible to annotator bias (Durden et al., 2016). The recent development of image-based catalogues of fauna and seascape features (e.g. Althaus et al., 2013; Howell et al., 2020) and, the integration of these typologies into web-based annotation tools of 2D images has been widely used to mitigate identification bias by standardizing and remotely reviewing the categorization of large annotation sets (e.g., Langenkämper et al., 2017).~~

~~For spatial investigation, the compilation of those annotations into space requires coordinates typically measured by a georeferencing device (e.g. GPS for terrestrial studies; ref). However, the lack of precision of image positioning inherited from underwater vehicle navigation considerably lowers the spatial resolution at which deep-sea investigations are performed. Commonly, a submarine platform gets its position from the ship through an acoustic signal (usually the Ultra Short Baseline system, USBL), whose precision decreases with depth. Depending on the system used and its calibration, the accuracy may range from 1% to 0.1% of the slant distance. At 1,000 m depth, the accuracy of the position is in the range of 1 m to 10 m. Recent advances in computer vision can provide access to an optimal repositioning (i.e. precision < 1 m) of underwater vehicles based on sequences of overlapping images. For instance, using photogrammetry, images can be re-assembled using feature-matching algorithm also refining *a posteriori* the position of the underwater camera. As a result, the relative positioning of features over the resulting 3D model of the seabed can be as precise as 1 cm or even less (Palmer et al., 2015; Istenič et al., 2019). Furthermore, a 3D model provides a numerical terrain model (NTM) from a centimetric to millimetric precision, enabling a high-resolution mapping of the seabed~~

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~~bathymetry from which geomorphometric descriptors, such as slope and rugosity, can be rapidly and mathematically derived (Wilson et al., 2007; Gerdes et al., 2019). Those objectives terrain metrics are especially of importance when considering them as explanatory variables for ecological investigation (Robert et al., 2017; Price et al., 2019). In addition, with the development of computer vision and photogrammetry, an overlapping image set allows reconstructing underwater scenes in three dimensions, advancing seascape ecology from 2D to 3D (Kwasnitschka et al., 2013; Lepczyk et al., 2021).~~

~~However, the georeferencing system of 3D models conflicts with the acoustic-based relocation of annotations made on 2D images, hence producing two spatially incompatible datasets. A possible solution to cope with the mismatch between an acoustic-based positioning inherited from vehicle navigation and an optical-based positioning inherited from photogrammetry would still be to annotate the 3D model or the derived orthomosaics, instead of raw images. However, 3D models and associated orthomosaics typically lower the resolution of the raw 2D images, eventually flattened over the mesh, hence reducing the detectability of small organisms and possibly, biasing the observed community composition (Thornton et al., 2016). Because we identified the lack of existing method to mutualize the benefit of 2D image annotation on web-based annotation tool and photogrammetric outcomes (i.e. optimal navigation and objective terrain descriptors), we propose a new and innovative workflow to transform 2D annotations in a 3D georeferencing system (Marcillat et al., 2023). This involves the development of a function allowing re-projection of annotations made in the open-access web-based image annotation tool Biigle (Langenkämper et al., 2017) onto 3D models produced with the freely available photogrammetry software Matisse3D (Arnaubec et al., 2023). The precision of the method has been assessed in different deep seascapes, with different camera settings and vehicles, and has been compared to an available georeferencing method from Biigle. Furthermore, we explored the use of this workflow for overlap management in image set building.~~

Materials & Methods

Study sites

Four ~~datasets~~data sets were used to assess the accuracy of annotation reprojection onto 3D models (Table 1). The four ~~datasets~~data sets represented different geological settings acquired using two different vehicles~~ and cameras. Downward~~. A downward-looking ~~cameras were~~Nikon D5500 camera was mounted on the remotely operated vehicle (ROV) Victor 6000 to map three hydrothermal vent sites and on the hybrid remotely operated vehicle (HROV) Ariane to map a cold-water coral (CWC) reef.

On Victor and Ariane vehicles, underwater navigation is achieved through advanced sensor fusion techniques. Both vehicles employ a suite of similar equipment. A 600kHz RDI DVL (Doppler Velocity Log) is utilized for precise velocity measurements and altitude estimation from the seabed. Absolute acoustic positioning is achieved using either the Posidonia 6000 or GAPS systems. Gyrofiber INS technology, such as the Phins from EXAIL, is employed to

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capture angle, angular velocity, and acceleration data. Depth measurements are obtained using Paroscientific sensors. These various navigation sensors are seamlessly integrated and processed by the INS Kalman filter, resulting in state-of-the-art acoustic/inertial navigation accuracy.

The underwater vehicles were flown at a constant altitude to acquire parallel photo transects to map the ~~active vent chimneys and periphery as well as the CWC reef.~~respective seafloor structures of the four sites. Tui Malila is a hydrothermal vent field surrounded by a complex basalt field and ~~is substratum~~ located on a fast ~~dorsal~~spreading ridge in the center of the Lau back-arc basin (South-West Pacific; ~~ref).~~Hourdez & Jollivet, 2019). The modelled area is a rectangle of 250 m by 10 m (Fig. 1.C). Eiffel Tower and White Castle are two vent edifices ~~surrounded by~~on a ~~mild~~ gentle slope ~~terrain consisting~~ mainly made up of ~~slab~~volcanic talus and are located in the Lucky Strike vent field on the Mid-Atlantic Ridge ~~(Ondréas et al., 2009)~~(Ondréas et al., 2009). At the periphery of the Eiffel Tower edifice, the modelled area is a rectangle of 120 m by 10 m (Fig. 1.D) and at the periphery of White Castle a rectangle of 115 m by 30 m (Fig. 1.B). The ~~most recent~~last ~~dataset~~data set was acquired in a cold-water coral reef located on a large (~~10s of meters~~150 m by 50 m) and mostly flat terrace in a submarine canyon of the Bay of Biscay. The modelled area is a linear transect of 65 m long by 2.5 m width (Fig. 1.A). The reef consists of isolated colonies of *Madrepora oculata* growing on a matrix of dead ~~coral~~corals infilled with soft sediments.

Table 1: Different ~~datasets~~data sets used during the reprojection error evaluation.

3D reconstructions ~~and image annotations~~

~~For each of the four datasets, 3D models were reconstructed using Matisse3D (Arnaubec et al., 2023). Prior to reconstruction and annotation, the images were corrected for underwater attenuation and non-uniform illumination using the Matisse3D preprocessing module in order to improve feature matching outcome. For the reconstruction, images were also resized to 4 Mpx to improve reconstruction speed.~~

For each of the four data sets, 3D models (i.e. textured 3D meshes) were reconstructed in Matisse3D using the 3D Sparse FASTEST processing (Arnaubec et al., 2023). Prior to reconstruction and annotation, the images were corrected for underwater attenuation and non-uniform illumination using the Matisse3D preprocessing module in order to improve feature matching outcome. Images were also ~~resized~~downscaled to 4 Mpx to speed up the reconstruction process.

Matisse3D performs feature detection and matching using the SIFT algorithm and removes outliers using the RANSAC model based on the fundamental matrix ~~(see Arnaubec et al., 2015).~~(Arnaubec et al., 2015). Bundle adjustment then uses the images to reconstruct the 3D points detected by the SIFT algorithm. During bundle adjustment, the position of the camera relative to the scene is ~~modeled~~modelled and georeferenced by ~~fitting~~ minimizing the difference between these camera positions ~~to~~ and those provided by the navigation system without altering the relative positions of the cameras in the bundle. The georeferenced camera positions

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~~computed during~~resulting from the bundle adjustment ~~is~~ are hereafter referred to ~~here~~ as the optical navigation. The number of points in the model is then increased using the dense matching method in openMVS (Cernea, 2020) to create a dense cloud. Finally, ~~the~~ a 3D mesh ~~surface~~ is ~~reconstructed~~ generated using the Poisson surface reconstruction algorithm using the default values of the user parameters in openMVS and then textured using…. The resulting 3D models (textured mesh) have an average resolution of 5 mm.

~~Optical navigation can differ significantly from the raw navigation. Disjoint images were selected from the ROV dive on Tui Malila vent site using the disjoint mosaic function of Matisse3D (non-overlapping image georeferencing using raw navigation and altitude data). All disjoint images were annotated for fauna (e.g. on each images, all recognizable individuals were tagged with points, and all patches delimited with polygons) using the image annotation web service Biigle (Langenkämper et al., 2017). We then investigated the effect of inaccuracies in the raw navigation on the quality of the annotations by estimating image overlap and annotation duplicates.~~

~~For the purpose of reprojection error evaluation~~

Image annotations

Two sets of image annotations were used for two different purposes. To build the first ~~data~~ set, only images from the Tui Malila vent site were used. Disjoint images (images whose footprint do not overlap) were selected using the disjoint mosaic function of Matisse3D. The function uses the hybrid navigation and the altitude of the ROV to map all images, then maximizes the number of theoretically non-overlapping images based on ROV-navigation. All these disjoint images were annotated for visible fauna (i.e. on each image, all recognizable individuals were tagged with points, and all faunal patches were delimited with polygons) using the image annotation web service Biigle (Langenkämper et al., 2017). This disjoint-image ~~data~~annotation set was used to illustrate the mismatch in image positioning between the acoustic navigation and the optical navigation, and its consequences on annotation georeferencing (e.g., double counting of some individual organisms and unnecessarily duplicating the annotation effort).

To build the second ~~data~~ annotation set, a subset of 20 images was randomly selected ~~in~~from each of the four ~~dataset~~study sites and ~~manually~~visually checked for non-overlap. On each image, four recognizable features were annotated with points using Biigle. ~~Annotations~~These points ~~have been~~were chosen carefully to ensure that they are evenly distributed throughout the image. Coordinates for all annotations in the image were then exported from Biigle ~~using the csv~~in a format that provides individual positional information (i.e. the CSV report scheme~~.~~, see Biigle manual). These points are ~~hereafter~~hereinafter referred to as “~~ground~~2D control~~”.~~ points”. This control data set was used to assess the accuracy of the reprojection method (see below).

Figure 1: 3D reconstructions used during this study

A: Coral Garden, B: Periphery of White Castle vent site, C: Tui Malila vent site, D: Periphery of Eiffel Tower vent site.

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Annotation reprojection

~~The annotations were re-projected onto the 3D model using the camera position and rotation information from the 3D model and the intrinsic characteristics of the camera. This information is stored in a *sfm_data* binary file generated by 3D reconstruction library implemented in Matisse3D, OpenMVG (Moulon et al., 2016). For the reprojection, the cameras line of sight were simulated using the Blender python library (Blender Community, 2018) and the Blender Photogrammetry Importer (Bullinger, Bodensteiner & Arens, 2023). The annotation pixels were then projected onto the 3D model using ray tracing (Figure 1). For each of these pixels, a ray is launched from the viewpoint in the 3D scene containing the 3D model. The 3D reprojected position corresponds to the first intersection between the ray and the model. If the reprojected annotation is a polygon, each vertex of the polygon is reprojected. If the ray does not hit the model, e.g. if the corresponding area in the image is not properly modeled, the annotation is discarded (Figure 1). A Python implementation of this process has been develloped: (Marcillat et al., 2023).~~

~~**Figure 1**~~The images and/or the annotations from the disjoint and control data sets were re-projected onto the 3D models using the camera position and rotation information (the extrinsic parameters) and the optical characteristics of the camera (the intrinsic parameters) resulting from the photogrammetric reconstruction. This information is stored in a ~~sfm~~_data ~~binary~~ file generated by OpenMVG (Moulon et al., 2016), ~~that~~ which is the 3D reconstruction library implemented in Matisse3D. For the reprojection of each camera's line of sight, we used the Blender Python Library (BPL, Blender Community, 2018) and the Blender Photogrammetry Importer (Bullinger, Bodensteiner & Arens, 2023). In this process, the annotation features were then projected onto the 3D models using the ray tracing implementation in BPL (Fig. 2). For each of these features, a ray is ~~launched~~shot from the camera viewpoint towards the 3D model based on the image coordinates of the feature. The 3D reprojected position of a 2D feature corresponds to the first intersection between the ray and the model. If the reprojected annotation is a polygon, each vertex of the polygon is reprojected. If a ray does not hit the model, for example if the corresponding area in the image is not properly modelled, the annotation is discarded (Fig. 2). A Python implementation of this process ~~has been developed (Marcillat et al., 2023)~~is available from https://github.com/marinmarcillat/CHUBACAPP.

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Figure 2: Principle of ~~annotations~~annotation reprojection
The camera corresponding to an annotated image is positioned and oriented in the 3D model referential and its optical characteristics are set according to the sfm_data binary file. For each annotation on the 2D image, a corresponding ray is ~~launched~~shot towards the 3D model. Green: Successful point annotation reprojection. Blue: Successful polygon reprojection (each point of the polygon contour is reprojected). Orange: The ray missed the 3D model, the reprojection is unsuccessful.

The local 2D uv coordinates of the ~~annotations (in pixels, 2D)~~features in the images were thus transformed into global coordinates (georeferenced~~:~~ using the WGS84~~, 3D~~ datum). The ~~imprint~~footprint of each image ~~on~~from the ~~3D model~~disjoint data set was also determined as a 3D ~~polygons~~polygon by reprojecting the image ~~edge pixels~~corner coordinates in the same way as the annotation points.

~~Error evaluation~~

~~Reprojection~~

Evaluation of annotation duplicates and reprojection accuracy ~~was assessed by finding back~~

The analysis of the ~~ground~~disjoint image data set and control data set was conducted using the open-source visualization software Blender (Blender Community, 2018). In both cases, the corresponding textured 3D models were imported.

To determine the percentage of duplicates in the fauna annotations of the disjoint image data set, these annotations were reprojected onto the 3D model and imported into Blender. When two reprojected annotations of the same species were in close proximity, the annotations on the original images were compared to assess whether they were of the same individual. The percentage of duplicated annotations was then calculated. To illustrate the areas of overlap, the ~~im~~footprint of each image (i.e. a polygon corresponding to the entire image) was also reprojected onto the 3D model.

To evaluate the accuracy of reprojections, the 2D reprojected control points from the control data set were imported into Blender. The features in the images corresponding to these 2D control points were visually identified within the ~~textured 3D models.~~texture of the models. These points are hereinafter referred to as 3D control points. The distance between ~~features on the textured 3D model and the same features after reprojection was measured~~2D reprojected control points and 3D control points was determined by comparing the 3D coordinates in Python using the Euclidean distance ~~in 3D (Figure 2~~(Fig. 3). The distance is used as a proxy for the error measurement of the annotation reprojection. For each dive, the median Euclidean distance between 2D control points and 3D control points was computed together with the interquartile range (i.e., IQR, the difference between the first and third quartile). The IQR is a measure of statistical dispersion.

~~To compare this method with the annotation geolocation available in Biigle (georeferencing based on the ROV's raw navigation, heading and elevation), annotation location reports of the ground controls were generated in Biigle. These geolocated positions were then compared to the reference positions on the 3D textured models, and the distance calculated.~~

Figure ~~2: Error~~3: Reprojection accuracy evaluation process.
A: Annotation of a recognizable feature (2D control point) on the 2D raw image in Biigle~~.~~ ~~Measurement on the 3D~~ (here, a cubic shape of the Tui Malila dive site). B: Reprojection of this

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2D control point onto the textured 3D model ~~of the reprojection error as the distance between the reprojected annotation point and the reference~~. C: The position of the feature ~~on the~~ annotated as a 2D control point is localized on the textured 3D model (“3D control point”, red point), and the distance with the 2D reprojected control point (green point) determined.

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Results

~~Raw~~Hybrid versus optical navigation

The ~~comparison~~ discrepancy in image georeferencing between the hybrid and optical ~~and raw~~ navigation ~~from the Chubacarc dive~~is illustrated on ~~Tui Malila vent site allows highlighting~~ Fig. 4 with the ~~discrepancy between raw image positioning, based on raw~~disjoint data set. According to the hybrid navigation, images were aligned along three roughly parallel transects (Fig. 4.A and ~~3D model positioning based on~~ B). According to the optical navigation ~~(Figure 3). Transects that should be parallel~~ however, the ~~relative~~ distance between ~~images and separated by~~the supposedly parallel-transects decreases towards the west end (Fig. 4A). As a ~~fixed distance are actually overlapping in some cases. Consequently,~~result, the ~~im~~footprint of images that were supposedly ~~non-overlapping~~disjointed according to the ~~raw~~hybrid navigation (Fig. 4.B) actually overlapped on the textured 3D model ~~(Figure 3),~~, and 29% of the annotations were duplicated~~.~~ (Fig. 4.C).

Commented [GC21]: You called this ‘acoustic’ earlier. Pick a choice and stick to it throughout.

Commented [GC22]: Or whatever that left end is, see comment on Figure 4.

Commented [GC23]: See earlier comment about duplicates

Figure ~~3~~4: Impact of navigational inaccuracies.
(A) Discrepancy between ~~raw~~hybrid navigation and optical navigation (from photogrammetry). (B) 2D disjoint mosaic obtained ~~from raw~~with Matisse3D using hybrid navigation data. Three annotations, visible across several images, are shown separated by colored lines with the corresponding horizontal distance in meters. (C) ~~Imprints~~ Footprints of the same images reprojected onto the photogrammetric model. ~~Disjoint images of the 2D mosaic actually overlap~~The duplicated annotations are represented with corresponding color crosses.

Commented [GC24]: I would add a North arrow to figure 4a to make clear is a (horizontal) map and not a graph. Then you can say in the text that the 3 dive lines (what you call transect) merge at the west end (or whatever cardinal direction that is).

~~For the four datasets, the distance between the geolocalised ground controls, based on raw navigation, and their reference positions on the 3D model further highlight the discrepancy between raw and optical navigation (Figure 4). The median distances were comparable among datasets, ranging from 2.35 m at White Castle to 4.67 m at the coral garden. The offsets were however variable within datasets. The interquartile ranges (IQR) varied from 2.57 m at Eiffel Tower to 3.28 m at the coral garden. The differences were unrelated to the vehicle. The median distance and IQR were comparable at the coral garden, mapped with HROV, and the three vent sites mapped with the ROV.~~

~~**Figure 4**~~

Annotation reprojections

Figure 5: Distribution of log-transformed distances between annotations of ~~ground~~2D control points on raw images and their ~~reference positions~~corresponding 3D control points

Commented [GC25]: Are you using a natural logarithm or one in base 10? I assume the latter. However, some readers may interpret the ‘e’ as Euler's number. Better put all the tick marks in cm (so you would have 0.01, 0.1, 1, 10, and 100 (1m). Because most distances are in the order of cm, it is best to use cm as the units.

on 3D models for different sites~~, according to two georeferencing methods: (A) geolocalisation based on raw navigation, and (B) reprojection based on optical navigation.~~

~~Annotation reprojections~~

~~Of the~~ A total of 320 ~~ground~~ 2D-control points ~~that~~ were annotated on the raw images to assess the precision of reprojections, of~~f~~ which 293 could be successfully reprojected onto the 3D ~~model~~models. The reprojection computing took less than 10 seconds to complete. Points that failed to reproject mostly corresponded to imperfections in the 3D models (17 missing points at Tui Malila, 5 at Eiffel Tower, 3 at the coral garden, and 2 at White Castle). ~~For instance, where there are 'holes' (non-reconstructed areas in the model), light rays can pass through without hitting the model.~~

The distance between the reprojected ~~ground controls~~2D-control points and their reference position on the 3D models emphasize the ~~precision~~accuracy achieved by reprojection (~~Figure 4~~Fig. 5). The median distances at the coral garden (1.1~~*10e-2 m~~ cm), White Castle (~~9.6*10e-3 m~~0.96 cm), and Eiffel Tower (1.3~~*10e-2 m~~ cm) were similar, as well as their IQR, ranging from 1.2~~*10e-2 m~~ cm at White Castle to 2.3~~*10e-2 m~~ cm at Eiffel Tower. At Tui Malila, which is the ~~most~~ topographically most complex site, the median distance and the IQR were higher, at respectively 8.6~~*10e-2 m~~ cm and ~~2.1*10e-1 m.~~ 21 cm.

Discussion

~~In the context of growing interest for 3D seascape ecology (Lepczyk et al., 2021; Swanborn et al., 2022; Pulido Mantas et al., 2023), structure from motion (sfm) allows to reconstruct textured 3D models with centimeter resolution using underwater ROV/AUV imagery. Hereby, we present the first tool for reprojection of 2D annotation on 3D models. This tool implemented in a dedicated interface 'Chubacapp' provides multiple benefits for improving ecological investigations.~~

~~The resolution of 3D models allows generating small-scale geomorphometrics (e.g. slope, roughness, bathymetric position index…), which can provide new insights on species distribution patterns, especially in complex three-dimensional ecosystems and over continuous spatial scales (Price et al., 2019; Robert et al., 2020). However, the use of high-resolution environmental variables makes necessary the georeferencing of faunal observations with an equal precision that remains a challenge to reach for deep-sea studies. Annotation geolocalisation using raw navigation (using ROV position attitude and altitude) relies heavily on navigation precision. The distance we observed between raw-navigation based and optical-navigation based positioning, with a median positioning error across datasets of 3.01 m, is coherent with the acoustic navigation precision. The median error does not vary much between datasets but variations can be as high as 3.28 m within datasets. With such an approximation in the~~

Commented [GC26]: Per point or per dataset? Pl specify

Commented [GC27]: Before you were saying these imperfections were data gaps, which does happen often in the SfM depending on image overlap. 'Imperfections' is too vague, pl give a specific example.

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~~positioning of features on the deep seafloor, abiotic and biotic interactions occurring at scales lower than 10 m are out of our understanding.~~

~~Typically, as a result of the low navigation resolution, most seabed studies made use of annotations directly performed over continuous image sets either processed into textured 2D orthomosaics or 3D models in the case of complex environments (Pizarro & Singh, 2003; Marsh et al., 2012; Bodenmann et al., 2017; Simon-Lledó et al., 2019; Mitchell & Harris, 2020; Girard et al., 2020). On top of that, annotations of 3D models can~~

The advent of underwater photogrammetry has offered a powerful tool to study seascapes, with a resolution hardly achievable by means of acoustic mapping of the deep seafloor. The same images acquired with an AUV or an ROV can now be used to map biological and geomorphological features as well as to build DTM with a resolution in the order of centimeters to millimeters. However, while there exist powerful open-access tools for image annotation and 3D model building, we found it difficult to merge data from these two processing pipelines because of their mismatch in georeferencing. We illustrated this discrepancy by reprojecting the ~~im~~footprint of supposedly disjoint images onto a 3D model. The images, and the annotations on these images, were georeferenced using the navigation of the ROV, as is usually done when processing such data. Even though images were georeferenced using a state-of-the-art navigation system combining acoustic and dead-reckoning positioning, the supposedly disjoint images were in fact overlapping on the 3D model, resulting in ~~a redundancy~~duplication of almost a third of the annotations made on these images. This is due to the well-known inaccuracy of even the most accurate positioning systems. The consequences are three~~-~~fold~~s~~. First, the absolute positioning of a feature is known within a radius that equals the accuracy of the positioning, that is to say in the range of 1 m to 10 m. In the framework of seascape ecology, this may not be an issue if the accuracy is still higher than the resolution of the DTM on which the image data are mapped and against which they are analysed (Swanborn et al., 2022). But it becomes critical when the resolution of the DTM is an order of magnitude ~~lower~~higher than the accuracy of annotation positioning. In addition, the relative distance between images is also approximate, which is limiting the ~~interest~~ application of spatial autocorrelation analyses. Finally, ~~similar~~the same features may be annotated several times, which is a loss of time and can lead to spurious results if unnoticed.

To cope with this discrepancy we developed an open-access solution to reproject image annotations onto 3D models. Here, the position of the camera computed during the process of model building is used instead of the position of the camera given by the ROV navigation. In three of our study sites, image annotations, once reprojected, are positioned onto the 3D model with a median accuracy of about 1 cm compared to annotations made directly on the 3D model. Since the accuracy we achieved is similar to the resolution of the 3D model, the method allows to get the best of the two worlds, both annotations on images at full resolution with powerful annotation tools, and a true 3D DTM at very high resolution. Ultimately, this will facilitate exhaustive megafaunal community characterizations over large continuous spatial extents of

Commented [GC28]: Aerial photogrammetry has existed for almost a century, so you have to add this qualifier.

Commented [GC29]: Replace with “overestimation of relative abundance”? Or at least give an example of ‘spurious results’

100s of m2, as those large image sets are increasingly collected with autonomous underwater vehicles (Thornton et al., 2016).

At~~ be challenging due to the difficulty of displaying large high-resolution models and because of the longer duration required for drawing 3D geometries compared to 2D annotations. As a result, photogrammetry investigation typically focused on a subset of easily discernible organisms (e.g., Thornton et al., 2016) or on areas of a few 10s of m^2 (e.g., Lim et al., 2020; Mitchell & Harris, 2020). Moreover, during the texturing of photogrammetry outputs, images are distorted and the definition is lowered. Hence, smaller organisms may be missed, misidentified, and might require a time-consuming confirmation in the original image. To avoid biasing community composition insights, identification must be performed on the highest resolution of images and on an annotation platform allowing an easy and remote review by taxonomic experts (e.g., the largo tool in Biigle: Langenkämper et al., 2017).~~

~~As the tool developed in this study provided a satisfactory repositioning of annotations at the centimeter scale, it demonstrates its whole potential by combining the better of two worlds. From 2D annotations of higher-resolution taxa, it allows an optimization of annotation georeferencing on 3D continuous models of the benthic habitat. From textured 3D models, it allows an acceleration of the annotation process. Ultimately, this will facilitate exhaustive megafaunal community characterizations over large continuous spatial extents of 100s of m^2, as those large image sets are increasingly collected with autonomous underwater vehicles (Thornton et al., 2016).~~

~~It should be noted however that 3D models are not exempted from errors. In our datasets, 3% of image annotations could not be reprojected on 3D models due to model imperfections. Many improvements could be made to the quality of 3D models to avoid non-reprojected points. Manual transects can cause these gaps were the ROV is too fast or too high. "Survey" mode, the ROV autonomous guidance mode, has proven to operate more efficiently when mapping large areas in multiple transects, and should be generalized. However, this autopilot mode can be prone to Doppler Velocity Log (DVL) dropouts, particularly in complex terrains with large bathymetric variations. Topography can also drive erroneous reprojection of annotations over 3D models. In fact, the higher distance error (~ m) observed for~~ the Tui Malila site ~~dataset could be related to a higher topographic complexity~~however, the median accuracy was close to 10 cm and more variable than at the three other sites. Tui Malila is also topographically more complex than the other sites because of the rocky basaltic terrain exhibiting faults. Those faults could clearly limit the 'hit' of the ray ~~light~~ traced from the downward-looking camera in near vertical setting, ~~hence~~thus reprojecting the annotations a few decimeters away ~~in~~from the fault. ~~In the near future, specific 3D mapping instruments~~The accuracy and precision of the reprojection are thus dependent on the roughness of the terrain, and it would be best practice to assess its effectiveness.

Terrain roughness also has an influence on the quality of the 3D model. In our data sets, 3% of image annotations could not be reprojected on 3D models due to model imperfections, most of which at the Tui Malila site. The ROV was pre-programmed to run along parallel paths to

Commented [GC30]: Just a thought. Once you have enough (hundreds to thousands) of training instances, maybe the community of researchers could develop AI-based methods (e.g. deep convo networks like YOLO could draw boxes and identify the type of organism on the 2D images, which can them projected in the mesh and duplicates coming from different phots removed. We are doing that with trees an it works nicely… I now see you already have a comment along these lines at the end of the Discussion, that's good.

Commented [GC31]: I would replace this with "further research is required to quantify this effect". Or is it a caution to practitioners to check the accuracy? Then be more specific as how to do that.

optimize the image overlap needed for 3D reconstruction. In this "survey" mode, the ROV heavily relies on the DVL for its navigation but in complex terrains with large bathymetric variations bottom tracking may be lost, thus compromising the integrity of the survey. New technological developments such as LIDAR, multibeam scanning sonars or stereo camera ~~will~~are now significantly ~~improve~~improving the speed and the accuracy of ~~the~~3D reconstruction and the overall quality of 3D mapping, as well as providing ~~an accurate optical navigation~~a simultaneous mapping and imaging of the seafloor at centimetric scales (Caress et al., 2018). These methods produce 3D models, bathymetry and photomosaïcs that fully overlap, allowing the precise evaluation of species distribution in relation to topography (Barry et al., 2023). But while this mapping system requires specialized and costly equipment, reprojection can be utilized directly on most ROV, making it cost-effective.

~~Still, one of the main bottlenecks in faunal imaging studies remains the annotation step of 2D images (Matabos et al., 2017). For image and video annotation, many online and collaborative tools have emerged recently (e.g. Biigle: Langenkämper et al., 2017, Squidle+: Bewley et al., 2015, VARS: Schlining & Stout, 2006), and the latest developments in assisted feature annotation have been integrated (Zurowietz et al., 2018). Citizen science platforms (Deep sea spy (Matabos et al., 2018), Zooniverse (Simpson, Page & De Roure, 2014)) also allow a significant increase in the amount of images processed. Our ability to adapt the workflow with Biigle demonstrates that it is flexible to any of the annotation platform mentioned above. Furthermore, automated detection by machine learning looks very promising to speed up the process. Although some experiments on automatic recognition of 3D features have been carried out (De Oliveira et al., 2021), most detection models remain actually developed for 2D images and videos (Katija et al., 2022). Reprojection may allow the use of well-proven generic 2D image detection Convoluted Neural Networks (CNN) for 3D annotation generation and vice-versa. On the one hand, 3D reprojection positions could generate 3D annotation sets for machine learning training. On the other hand, once a feature has been manually annotated on a single image and reprojected onto the 3D model, that 3D position can be used to locate that feature back on images taken from different angles. Multiple crops of the same object could then be generated and served as a training dataset.~~

A strong bottleneck that remains in image analysis is the time needed for annotations (Matabos et al., 2017). For image and video annotation, many online and collaborative tools have emerged (e.g. Biigle: Langenkämper et al., 2017, Squidle+: Bewley et al., 2015, VARS: Schlining & Stout, 2006), and the latest developments in assisted feature annotation have been integrated (Zurowietz et al., 2018). Citizen science platforms (Deep sea spy: Matabos et al., 2018, Zooniverse: Simpson, Page & De Roure, 2014) also allow a significant increase in the amount of images processed. Our ability to adapt the workflow to Biigle demonstrates that in principle it ~~is flexible against any of~~could also be adapted to the annotation platforms mentioned above. Reprojection could also be useful for disjoint image selection. Overlapping images can be detected before annotation by reprojecting the image ~~im~~footprints and checking for

Commented [GC32]: Are those mosaics orthometric (map-like, with a constant cartographic scale)? If so, call them orthophotomosaics.

~~intersections~~overlap between these reprojections. Furthermore, automated detection by machine learning looks very promising to speed up the process. Although some experiments on automatic recognition of 3D features have been carried out (De Oliveira et al., 2021), most detection models remain actually developed for 2D images and videos (Katija et al., 2022). Reprojection may allow the use of well-proven generic 2D image detection Convolut~~ed~~ional Neural Networks (CNN) for 3D annotation generation and vice-versa. On the one hand, 3D reprojection positions could generate 3D annotation sets for machine learning training. On the other hand, once a feature has been manually annotated on a single image and reprojected onto the 3D model, that 3D position can be used to locate that feature back on images taken from different angles. Multiple crops of the same object could then be generated and serve as a training data set. Ultimately, fully 3D open-access and collaborative annotation of high-resolution textured 3D models appear as an ideal solution in terms of accuracy for the analysis of species microdistribution and biotic interactions. This is already possible with some commercial solutions such as VRGS (Hodgetts et al., 2015). However, the cost of manipulating 3D models in terms of computational and energy requirements must be taken into account. Large 3D models require significant amounts of memory and graphics processing power to manipulate, which may require dedicated computers and/or servers. By removing the need for 3D annotation and thus reducing the number of 3D models manipulations, our solution could provide a trade-off between accuracy and computational requirements.

Conclusions

This study demonstrated that ~~3D~~ underwater photogrammetry and ~~reprojected~~ 2D annotations projected onto a 3D seascape model have several advantages when combined, in particular:~~.~~

- ~~Annotated~~ Instead of working on orthophotomosaics of lower quality, the raw seascape images can be annotated~~,~~ using the popular and collaborative Biigle software~~, are raw and~~ at full ~~scale~~ resolution, allowing optimal morphospecies categorization.
- Image overlap and annotation duplicates ~~are avoided thanks to optical navigation. Annotations are precisely georeferenced to a centimetric scale.~~can be avoided by filtering overlapping images prior to annotations.
- The ~~annotation~~ positional accuracy of the 3D projection of the 2D annotations is compatible with the analysis of intraspecific and interspecific interactions.
- The 3D model provides access to high-resolution topographic metrics to ~~explain annotations~~quantify annotation distribution over ~~continuous~~several spatial scales. This technique could be applied on a very large scale to particularly complex terrains such as hydrothermal vents, canyons, cliffs, or coral reefs.
- By removing the need of annotating and manipulating 3D models, ~~W~~we expect the developed workflow to considerably ~~fasten~~speed up the generation of annotation ~~set~~sets for 3D and for deep-learning purposes.

Commented [GC33]: Yes, that was exactly the idea I was suggesting earlier about YOLO.

Commented [GC34]: Effort? Labor? Or do you mean that the GPU may crash because of the high power demand?

Commented [CG35]: IMPORTANT. You have not demonstrated that overlap can be avoided using the projected footprints of the SfM-aligned images. What you demonstrated is the opposite, that the procedure of selecting disjoint images from the hybrid navigation can lead to considerable overlap. As a matter of fact, some overlap will always be necessary to avoid data gaps. What you could do once you have identified the areas of overlap is to sequentially apply the inverse projection (from the 3D model to the aligned image) to mask out the portions of the image corresponding to areas of overlap with an already processed image. Perhaps the easier solution though is to provide the Mattise 3D disjoint function with the optical navigation instead of the hybrid one, and then remove duplicates that come from different images. If you want to make any claim on this, you would have to add some additional work in this regard (e.g., another pane in Figure 4 with the footprints of images selected as disjoint when the hybrid navigation is used). Or you can say: "Using the hybrid (original) navigation data to select disjoint images can lead to considerable overlap and therefore unnecessary duplication of effort. This can be avoided by using the optical navigation instead."

Commented [CG36]: Would it make sense to add 'spatial' before 'interactions'? I assume there can be 'interactions' where proximity is not relevant?

Commented [CG37]: Replace with 'organism'?

Commented [CG38]: Specify what you mean by "this technique" (your workflow? If so, what about the commercial tools like agisoft's?) and by "very large scale" (do you mean the extent of the site in hectares, or do you mean in considerably more sites than what is possible now? Consider rewording this bullet point and make sure that whatever you state I supported by your results.

Supplementary Materials

The Python implementation of annotation reprojection, as well as other useful tools such as 3D topographic metrics calculation, disjoint image selection or model inference import into Biigle, are available on GitHub ~~(Marcillat et al., 2023)~~(Marcillat et al., 2023). Images, navigation data and 3D reconstructions are available at https://www.seanoe.org/data/00879/99108/~~on request~~.

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