A Data Compression Module for the SUNSET Platform

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***Abstract*—In the last two decades, visual data acquisition in underwater environments has dramatically increased due to the need to face a wide range of challenges that still require further research, including site monitoring, seabed anomaly detection, object detection and classification, and many others. Most of these activities require frequent data acquisition and processing over time, even at different altitudes, view angles, and perspectives. Recent improvements of small-scale Autonomous Underwater Vehicles (AUVs), in terms of navigation time, automatic control, and onboard processing, are making these submersible vehicles particularly suitable for activities as those reported above. Moreover, thanks to their cableless navigation, limited size, and agility, small-scale AUVs (hereinafter simply AUVs) can reach sites otherwise inaccessible with other kinds of underwater vehicles (e.g., medium and large AUVs). The payload capacity of current AUVs allows us to equip them with different vision sensors, including Red Green Blue (RGB) camera and Side Scan Sonar (SSS). In this context, an open issue remains the efficient transmission of visual data from AUV through an underwater acoustic network to allow a remote workstation an online and/or real-time data processing. In this paper, a data compression module for the SUNSET platform is presented. The module is composed of a set of novel algorithms that enables compression of RGB and SSS information with and without data loss. The module also implements some novel features, including progressive compression and Region Of Interest (ROI) selection; the first used to gradually transmit the image data (e.g., sites in which the acoustic transmission is a hard task), the second used to transmit, with higher quality than the rest of the image, the items contained in a specific area. Exhaustive experiments on RGB and SSS datasets prove the effectiveness of the presented module.**

***Index Terms*—SUNSET, data compression, RGB images, Side Scan Sonar images, lossless, lossy, progressive, AUVs**

I. Introduction

Computer Vision is a well-known field of study that is playing a leading role in a wide range of practical application areas, including video surveillance, smart environments, robotics, and many others. Nowadays, indoor and outdoor environments as well as humanoids, air drones, ground vehicles, and mobile devices are equipped with different types of cameras (e.g., RGB, Time-of-Flight, thermal) that allow us to acquire, even in distributed camera networks, a huge amount of visual data to be processed, often in real-time, to accomplish several critical tasks, such as object tracking and classification [1], change detection [2], event recognition [3], and so on. Such speed in the transmission step is possible because these systems are often cabled by high-speed data transmission wires (e.g., twisted pair, coaxial, optical fiber) which allow visual data to be transferred in real-time. Even when the transmission occurs in cableless mode, e.g., between an aerial drone and a ground station, current wireless technologies (e.g., 4G, 5G) allow visual data to be transferred instantly. Everyday experiences regarding what just reported above are in the access of image and video streams by laptops with a wired connection or smartphones with wireless connection. Moving to underwater environment, the situation tends to get complicated. This is due to the fact that standard wireless connections (e.g. Wi-Fi) do not work, while a cabled approach will limit the execution of certain tasks to the length of the cable. Usually, in these cases, acoustic communication is used, but there is still a problem: the bandwidth. In underwater acoustic communication, the latter is very limited and it makes very difficult, if not impossible, to send multimedia data (e.g., pictures and videos) in real-time o near real-time. For this reason, and to avoid saturating the available bandwidth, the data to be sent must be compressed. In this paper, a novel image compression module designed and implemented in SUNSET Software Defined Communication Stack (S-SDCS) [4] is presented. The image compression module is composed of four image compression modalities. In detail, three algorithms are designed for RGB images and one for sonar images. The rest of the paper is structured as follows. In Section II, the current state-of-the-art in underwater image compression is discussed. In Section III, the proposed compression algorithms are presented. In Section IV, the results obtained with the proposed algorithms are shown. Finally, Section V concludes the paper.

II. Related Work

In recent years, lots of methods were proposed to compress underwater images, which can be divided into three main categories: transform-based methods, compressed sensing methods, and deep learning-based methods. Transform-based is a class of techniques which are extensively used in image compression. Linear transforms are involved into the mapper stages to change the pixels of the original image into frequency domain coefficients (called transform coefficients). The Discrete Cosine Transform (DCT) and Discrete Wavelet Transforms (DWT) are one of the most used transforms in image compression. Li et al. [5] employed a wavelet-based

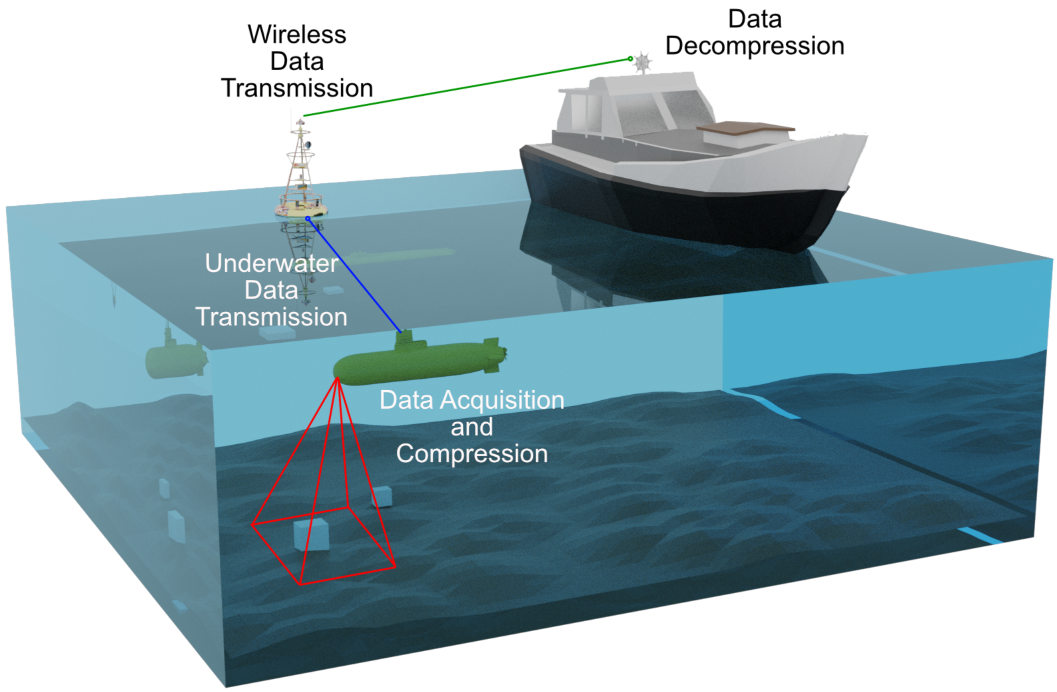


Fig. 1: Example scenario of underwater image compressing.

pre-processing method to remove the visual redundancy, and adopts a Wavelet Tree-based Wavelet Difference Reduction (WTWDR) algorithm to remove the spatial redundancy of underwater color images. Recently, Rubino et al. [6], an image compression algorithm based on a novel minimal time parallel DWT algorithm is presented. Another powerful class of methods is the Compressed Sensing (CS)-based where the sampling and compressing processes are synchronous instead of two independent as in the transform-based methods [7]. An interesting work is proposed in [8], where a new discrete-time image transmission system that combines compressed sensing techniques with non-linear mapping as analog joint source-channel codes is proposed. Another work is presented by Ya-Qiong et al. [9]. The authors have shown how the use of Bandlents transform allows saving important information of the sonar images in compressed-sensing algorithm. The last class of compression algorithms is the class of deep learning based methods. Zhuang et al. [10] proposed a novel algorithm that compresses the image texture and color separately for reducing the bit-rate. In [11], the authors have proposed a discrete wavelet transform (DWT) based deep learning model for image compression in Internet-of-Underwater-Things (IoUT).

III. Compression Modules

This section presents the image compression module composed of four different compression modalities. First, the three RGB compression modalities are presented, then the sonar compression process is discussed. In Figure 1, an example scenario is depicted. First, the AUV acquires the data to be compressed. The latter can be a standard RGB image or

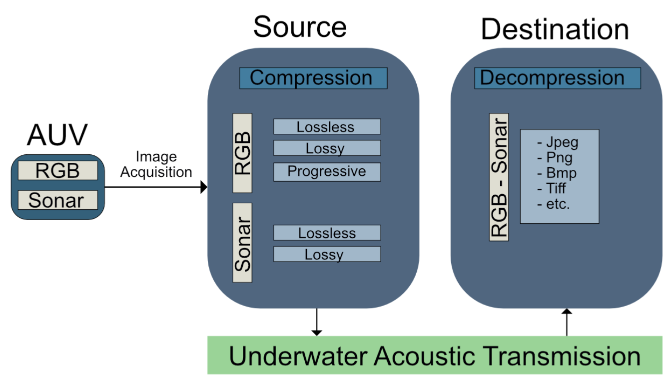


Fig. 2: Logical architecture of the underwater compression and decompression processes.

sonar data. Subsequently to the acquisition, the compression is performed allowing the transmission of smaller data in size. Then, through the underwater channel, the data are sent to a buoy, which acts as a gateway between the underwater and the standard wireless network. Next, the compressed data is sent to the destination (i.e., a boat) by using wireless connection (e.g., 4G or Wi-Fi). At the destination, the received data are decompressed and can be analyzed by a human operator. In Fig 2, the compression and decompression pipeline is depicted.

A. RGB Image Compression

In this section, the RGB compression algorithms and the corresponding parameters are described. In detail, the designed algorithms can be classified in the following 3 modalities:

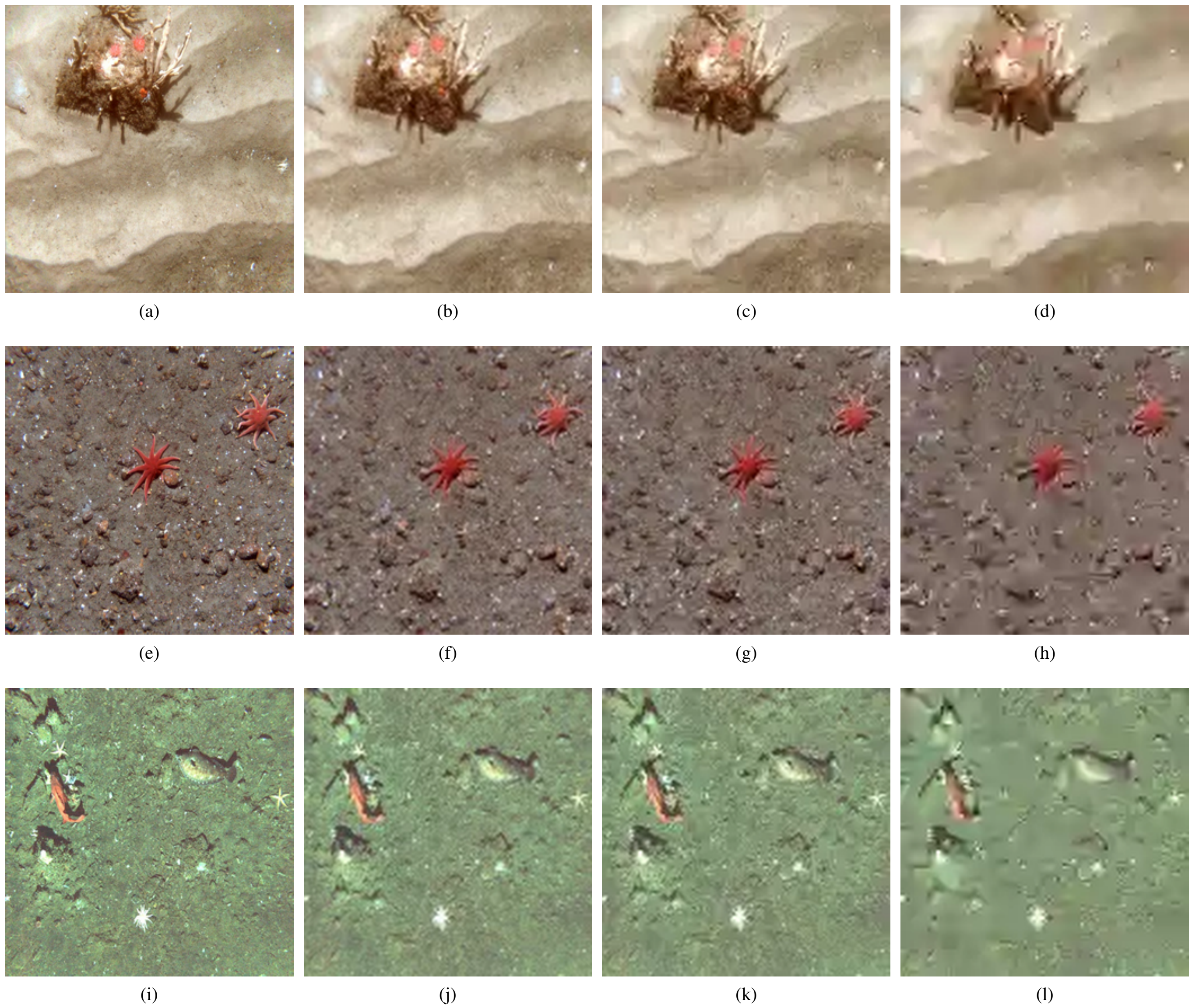


Fig. 3: Images compressed with the classic lossy approach. From the left we have a) the original image, b) the same image with a compression ratio of 10, c) the same image with a compression ratio of 50, and d) the same image with a compression ratio of 80.

- **Lossless Compression:** the original image and the one obtained from the decompression process are qualitatively identical, i.e. there is no loss in quality and information;
- **Lossy Compression:** the original image and the one obtained from the decompression process differ in quality and information. The amount of the differences depends on the used compression parameters;
- **Progressive Compression:** it is a lossy algorithm with the capability of providing a preview of the image. This is done by first sending an image with very few details, and then improving its quality and information by sending additional data that will be added to the first received image. The subsequent sent images are called *scan*.

For this type of images, the following steps are performed in the compression process: *transformation*, *quantization*, and *encoding*. In the transformation step, the image is pre-processed for optimizing the compression. In detail, the image can be downscaled for reducing its size (in terms of bytes) and dimensions (in terms of pixels), and it can be mapped to another color space (e.g., grayscale, HSV, etc.). Then, to ease the next step, the image is converted in frequency coefficients. In the quantization step, the less informative frequency coefficients are removed. This allows to achieve better compression results in terms of size, and since this step removes information, it is performed only for lossy algorithms. Finally, the encoding step is where effectively the image is compressed, obtaining the data ready to be sent. Concerning the decompression process, the following steps are involved: *decoding*, *de-quantization* and *inverse transformation*. The decoding step consists in reconstructing the original data stream before the encoding process. Once reconstructed, the data will be used as a starting point for the decompression. In the de-quantization step, the frequency coefficients are reconstructed trying to obtain the same number of coefficients available before the quantization. However, in lossy compression, the number of the coefficient will be smaller with respect to the number of coefficients generated in the compression process. Trivially, this is due to the fact that in lossy compression there is a loss of the original information. In the inverse transformation, the coefficients obtained in the de-quantization step are converted back to pixels. Subsequently, some post-processing such as super-resolution (needed to obtain the original dimensions in pixels of the image) and color reconstruction are performed. At the end of the decompression process, the image is stored in one of the common image format chosen by the user, e.g. jpeg, TIFF, png, and so on. Concerning the compression parameters, the followings are available:

- **Resize Factor:** is the parameter that allows to reduce, in terms of rows and columns, the size of the image to be compressed. It is used in the compression process;
- **Super-Resolution Factor:** is the parameter that allows to upscale the image. It is used in the decompression process;
- **Color:** is the parameter that allows to change the color space of the image. It is possible to choose between two color spaces, namely, RGB (composed by 3 channels) and grayscale (composed by 1 channel);
- **Compression Factors:** these parameters deal with the quantization step and modulate the result of the image reconstruction. The first parameter is the *quality*, which can have values in the range $[1, 100]$ where 1 is the worst and 100 is the best, while the second parameter is the *compression ratio*, which allows values in the range $[10, 100]$ where 10 consists in a smaller compression and 100 in a full compression.

B. Sonar Image Compression

As for RGB images, the sonar compression is composed of a compression and decompression process, which are described subsequently.

Regarding the compression process, in the sonar module, a further step in image acquisition is needed. In detail, the majority of sonar devices output data in raw format, which mainly has two problems. The first is that the raw data is usually sent in packets, which contain several data, e.g. header, control bits, etc., that increase uselessly the size of the packets. The second problem is that raw format is not human-readable, thus a human operator cannot directly work with the received data. So, the first step of the compression of sonar images consists in converting sonar raw data in a human-readable image. Then, the following steps are performed: *image transformation* and *compression*. Concerning the image transformation, it is the same step as the RGB images. In fact, it consists of downscaling the image so that the dimensions, in terms of pixels, are smaller than the original image.

Regarding the compression step, is composed of the following processes. First, the resized image is converted in the $\mathrm{YC_oC_g}$ color space. For this type of image, we found that this color space allows to obtain higher compression ratios. Subsequently, the Near-Zero Symbol Coding is used to convert the pixels value in binary notation. Then, the Meta-Adaptive Near-zero Integer Arithmetic Coding (MANIAC), which is a modified version of the well-known Context-adaptive binary arithmetic coding (CABAC), to compress the binary representation of the pixels. At this point, the sonar image is compressed and ready to be sent over the communication channel.

Concerning the decompression of sonar images, the first operation consists of reverting the binary image back to the $\mathrm{YC_oC_g}$ color space version. This is done by taking the image in Near-Zero Symbol Coding and applying the MANIAC inverse transformation. The second operation consists in changing the color space back to the original, namely the RGB. At this point, the decompression process is terminated but a further step may be needed. In detail sonar images, differently from the ones acquired with a standard camera, present a very high number of rows. This is due to the fact that the sonar acquires several time instants, generating a map of the seabed. This means that to achieve fast transmission of sonar images, the latter may be split into several smaller images and then recomposed at the destination. Hence, the further step consists of recomposing the several sonar images with the aim of obtaining the original image.

Also for the sonar compression module, some parameters can be set:

- **Resize Factor:** as for RGB images, is the parameter that allows to reduce, in terms of rows and columns, the size of the image to be compressed. It is used in the compression process;
- **Compression Factor:** is the parameter that deals with the quantity of compression. The higher the value, the more the image will be compressed, resulting in a smaller image (in bytes) but also with a lower quality. When set to 0, lossless compression is performed.

C. ROI Transmission

After that a received image has been analyzed by a human operator, the latter can request to the acquiring device a specific part of the received image at a higher quality in order to perform a more precise analysis. In detail, the operator draws a bounding box around the part of the image that is considered relevant. This process is performed through the Graphical User Interface (GUI) of the system. Then, the device used by the operator sends the bounding box data, i.e. top-left corner, width and height, to the device that has performed the acquisition. At this point, the acquiring device extracts from the original image the portion selected by the operator through the bounding box, performs the compression and sends back

TABLE I: Average PSNR, SSIM and size in bytes for standard compression approach.

Compression Ratio = 10			**Compression Ratio = 50**			**Compression Ratio = 80**		
PSNR	**SSIM**	**Size**	**PSNR**	**SSIM**	**Size**	**PSNR**	**SSIM**	**Size**
30db	70%	6662	28.3db	60 %	2576	27.7db	55%	1719

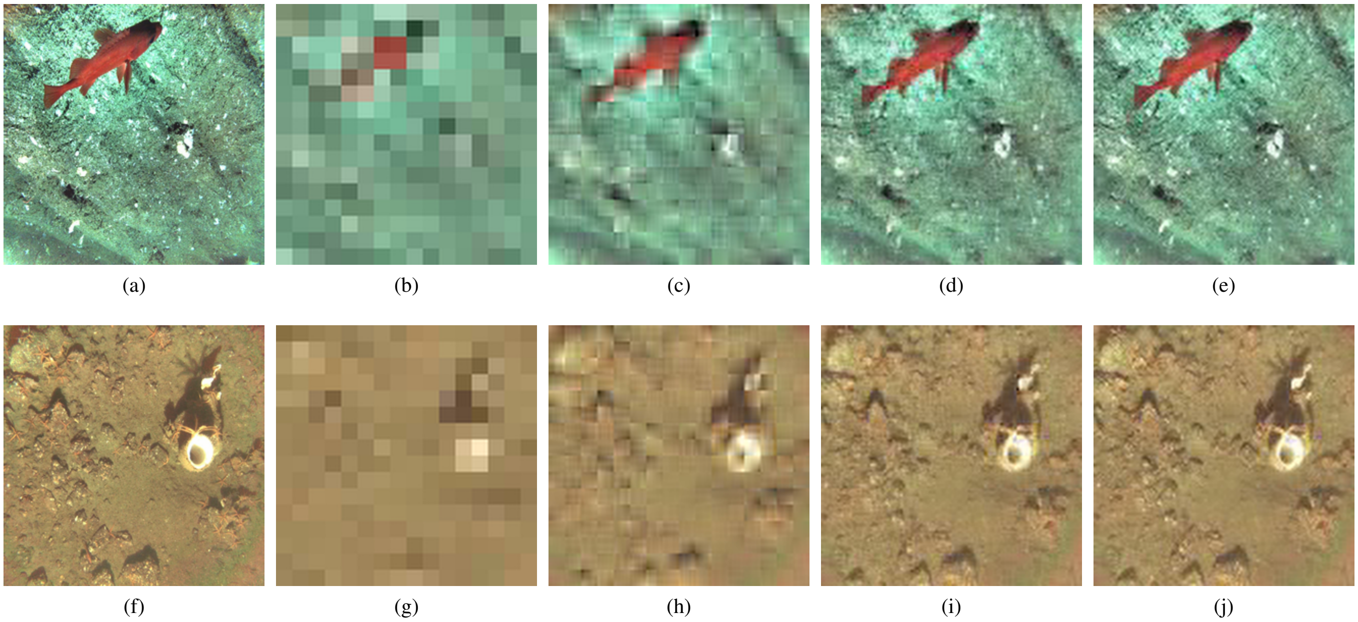


Fig. 4: Images compressed with the progressive approach. From the left, we have a) the original image, b) the first scan, c) the second scan d) the third scan and e) the last scan.

to the operator the new image, which contains the requested data at a higher resolution.

IV. Experiments

In this section, the results obtained with the proposed algorithms are discussed. Firstly, the results concerning RGB images are presented, then results regarding sonar images are discussed. Notice that, since the lossless compression will provide the same image as the original, only lossy approaches will be discussed. For testing RGB compression algorithms, the dataset provided by Humanant Singh Lab[1] has been used. It is composed of several images acquired from underwater environments related to fisheries, coral reef ecology, and other applications. For these experiments, we use a subset of this dataset composed of 50 underwater images having a resolution of $1280X1024$ pixels. As a measure for the quality of the decompressed images, both Peak Signal To Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) are used. For sonar images, the dataset available at [12] has been used. Due to the high noise present in this type of images, measure quality such as PSNR and SSIM cannot be used. Instead, qualitative results are presented.

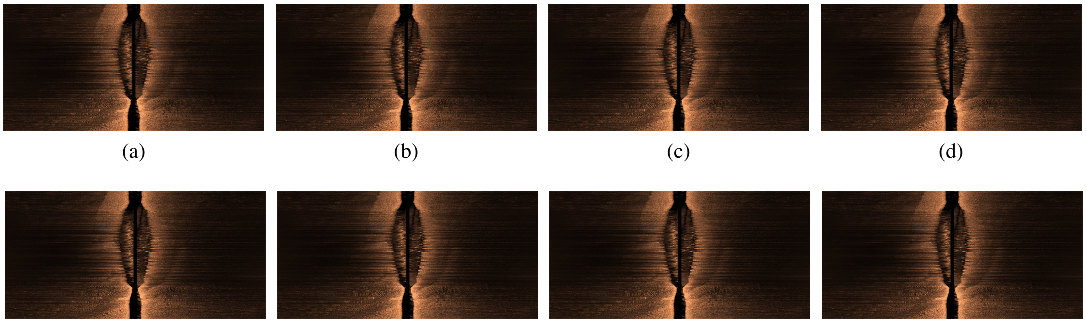
A. Results on Standard Compression Approach

Concerning the lossy modality, in Fig 3 some results on different seabed images are shown. In detail, we have the original image at the leftmost position, while we have the image compressed with a compression ratio of 10, 50, and 80, respectively, on the subsequent columns. For the quality parameter, in the first row it is set at 10, for the second row it is set at 30, while for the last row it is set to 50. As expected, by increasing the compression ratio the quality of the image decreases. Let us consider the rightmost image of the first row, which is the one with the highest compression ratio. Despite it is possible to see that something is present in the acquired scene, it is not possible to discern what it has effectively acquired. By considering the same rightmost image at the second and third rows, the situation is slightly better due to the higher quality parameter value but there are still several artifacts that make it difficult to understand what type of object has been acquired. In Table I, the average PSNR, SSIM, and sizes of the images are reported. In the performed experiments, we have found a very large gap between the size of the images compressed with a compression ratio set at 10 and the compression ratio set at 80. In some cases, such as the one of the third image (i.e. the third row of the table) we obtain a dimension in bytes smaller by 77.91%, which is impressive. However, the visual quality of the compressed images is strongly affected by this amount of compression. Hence, the right trade-off between quality and bytes size must be carefully chosen.

[1]https://web.whoi.edu/singh/underwater-imaging/datasets/

TABLE II: Average PSNR, SSIM and size in bytes of the images relative to the progressive approach.

Scan 1			Scan 2			Scan 3			Scan 4		
PSNR	**SSIM**	**Size**	**PSNR**	**SSIM**	**Size**	**PSNR**	**SSIM**	**Size**	**PSNR**	**SSIM**	**Size**
27.2db	47%	1117	28.8db	60.7%	1766	29db	64%	629	29db	64%	164



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 5: Example of a sonar image compressed with several compression ratios: a) original image, b) compression = 10%, c) compression = 20%, d) compression = 30%, e) compression = 50%, f) compression = 70%, g) compression = 85% and h) compression = 95%.

B. Results on Progressive Compression Approach

Regarding the progressive approach, in Fig 4 some examples of the obtained results are shown. For the first image, the used parameters for quality and compression ratio are, respectively, 80 and 10. For the second image, instead, the used quality and compression ratio values are 80 and 50. As it is possible to see, the first scan sent to the destination (Figs 4b) and c)) presents very low detail. This is due to the fact that the first scan is intended as a preview of the image. In detail, if the human operator finds something relevant within the preview image, he can ask the system the subsequent scans to improve the quality of the received image for having a better overview of the situation. This approach allows to always use the minimum amount of bandwidth available, since the several scans are smaller with respect to sending a whole compressed image, as shown in Table II.

The advantages of using the progressive approach are twofold. The first is that, as already stated, the used bandwidth is less with respect to the standard compression approach. The second approach is that the received image, after the reception of all the scans, will have a higher quality with respect to the one compressed with the standard approach.

C. Sonar Image Compression

Finally, in Fig 5 an example of compression of sonar image is depicted. As it is possible to see, for this type of image is possible to use higher compression ratios with respect to RGB images. This is mainly due to two reasons. The first is that sonar images are one channel images. This means that there is less information to compress, allowing to achieve better results in size. The second is that in sonar images there is a large amount of noise, meaning that most of the information lost during the compression is probably noise. Notice that we are still investigating this last point, and the assumption has been made on the basis of the performed experiments. In Table III, the size of the sonar image compressed with several compression ratios are reported. By considering the highest compression ratio, i.e. 95%, the size of the original image has been decreased by the 76.63%, which is again an impressive result. Differently from RGB images, the quality of the compressed images is (visually) higher. This is due to the fact that, with respect to RGB images, sonar images contain less information, making the decompression process easier. Notice that this is true only if the sonar image is not downscaled before the compression. If this is the case, the quality of the decompressed image will be affected. In fact, by reducing the image dimensions in terms of rows and columns, some information will inevitably be lost.

V. Conclusions

In this paper, a novel module for the S-SDCS able to perform the compression of images is presented. The module consists of three modalities for the compression of RGB images and one algorithm for the compression of sonar images. The three RGB compression algorithms fall in the following three categories: lossless, lossy, and progressive. The lossless approach provides a decompressed image equal to the original, but with a relevant size in terms of bytes and with high transmission time. The lossy approach provides a compressed image with a smaller size in bytes at the expense of the quality. The progressive approach provides a compressed image progressively, allowing to reduce the used bandwidth during the transmission and to have a decompressed image of better quality with respect to the lossy approach. Regarding sonar image compression, only lossless and lossy approaches can be used for the compression. Experiments on underwater RGB and sonar datasets highlight the effectiveness of the designed algorithms.

TABLE III: Size in bytes of the compressed sonar images at different compression ratios.

Original Image	**compression = 10%**	**compression = 20%**	**compression = 30%**	**compression = 50%**	**compression = 70%**	**compression = 85%**	**compression = 95%**
1.07 MB	980 KB	782 KB	695 KB	494 KB	385 KB	295 KB	250 KB

REFERENCES

[1] D. Avola, L. Cinque, G. L. Foresti, C. Massaroni, and D. Pannone, "A keypoint-based method for background modeling and foreground detection using a ptz camera," *Pattern Recognition Letters*, vol. 96, pp. 96–105, 2017.

[2] D. Avola, L. Cinque, G. L. Foresti, N. Martinel, D. Pannone, and C. Piciarelli, "A uav video dataset for mosaicking and change detection from low-altitude flights," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pp. 1–11, 2018.

[3] D. Avola, M. Bernardi, and G. L. Foresti, "Fusing depth and colour information for human action recognition," *Multimedia Tools and Applications*, vol. 78, no. 5, p. 5919–5939, 2019.

[4] M. Bernardi, C. Cardia, P. Gjanci, A. Monterubbiano, C. Petrioli, L. Picari, and D. Spaccini, "The diver system: Multimedia communication and localization using underwater acoustic networks," in *2019 IEEE 20th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*, 2019, pp. 1–8.

[5] Q.-Z. Li and W.-J. Wang, "Low-bit-rate coding of underwater color image using improved wavelet difference reduction," *Journal of Visual Communication and Image Representation*, vol. 21, no. 7, pp. 762 – 769, 2010.

[6] E. M. Rubino, A. J. Álvares, R. Marín, and P. J. Sanz, "Real-time rate distortion-optimized image compression with region of interest on the arm architecture for underwater robotics applications," *Journal of Real-Time Image Processing*, vol. 16, no. 1, pp. 193–225, 2019.

[7] J. Zhang, Q. Xiang, Y. Yin, C. Chen, and X. Luo, "Adaptive compressed sensing for wireless image sensor networks," *Multimedia Tools and Applications*, vol. 76, no. 3, pp. 4227–4242, 2017.

[8] I. Iglesias, A. Song, J. Garcia-Frias, M. Badiey, and G. R. Arce, "Image transmission over the underwater acoustic channel via compressive sensing," in *2011 45th Annual Conference on Information Sciences and Systems*, 2011, pp. 1–6.

[9] C. Ya-Qiong, C. Wei-Ling, and Y. Fei, "Underwater acoustic image compressive sensing algorithm research based on bandelets transform," in *OCEANS 2016 - Shanghai*, 2016, pp. 1–5.

[10] M. Zhuang, Y. Luo, X. Ding, Y. Huang, and Y. Liao, "A robustness and low bit-rate image compression network for underwater acoustic communication," in *Neural Information Processing*, T. Gedeon, K. W. Wong, and M. Lee, Eds. Cham: Springer International Publishing, 2019, pp. 106–116.

[11] N. Krishnaraj, M. Elhoseny, M. Thenmozhi, M. M. Selim, and K. Shankar, "Deep learning model for real-time image compression in internet of underwater things (iout)," *Journal of Real-Time Image Processing*, pp. 1–15, 2019.

[12] J. Anderson and B. Hallet. Raw towed sidescan sonar data (xtf format) acquired along the chilean inland passage fjord during the nathaniel b. palmer expedition nbp0505 (2005). [Online]. Available: http://get.iedadata.org/doi/306159