

Phase Contrast Enhancement Combined with Dark Channel Prior for Underwater Target Recognition

Khadidja Ould AMER
ISEN Brest Vision Lab

Marwa ELBOUZ
ISEN Brest Vision Lab

Ayman ALFALOU
ISEN Brest Vision Lab

Abstract: The major obstacle to the detection and identification of objects in underwater images is often due to their poor quality. Underwater images are known to be strongly degraded by light absorption and scattering. It is therefore very important to improve the quality of the images to facilitate the objects detection. For this purpose, we propose to combine a hardware and software techniques for image quality improvement. The first by using a polarimetric imaging optical system to reduce the scattering effects when acquiring images. The second by apply a Dark Channel Prior (DCP) dehazing method to the obtained polarized images. This approach has the advantage to be fast and efficient, because it does not require many software processing to improve the image quality. In this paper we validate our approach by introducing it into a complete process of target identification based on phase contrast enhancement and target recognition. Experiments carried out in our laboratory have shown that this approach greatly improves the target identification.

Keywords: Underwater image, Polarization, Image dehazing, Correlation, Phase contrast

Introduction

In recent years, the exploration of the underwater environment has drawn wide attentions. It is motivated by the technological advances of underwater imaging systems. The video camera has become a standard tool for underwater vehicles to observe and analyze the seabed. These vehicles are often guided from the surface by a human operator (ROV: Remote Operated Vehicle). However, this human intervention makes the processing long, and dangerous. These problems can be avoided by the use of autonomous underwater vehicles (AUV). However, in both cases the automatic analysis of images are limited by the poor quality of underwater images which decreases the performance of image processing algorithms. Indeed, the degradation of the underwater quality images is due to the absorption and scattering of light in the water. These two phenomena are related to the water turbidity [1]. Therefore, the underwater image is affected by one or more of the following problems: low contrast, reduced visibility, non-uniform illumination, attenuated colors, blur, and noise [2]. These problems modify the scene properties and complicates objects detection and identification. It is therefore important to improve the quality of the images in order to facilitate the identification of objects. In this context, many techniques of restoration and quality improvement of the underwater images have been proposed [3]. Restoration techniques consist in modeling the degradation that affect the image during it acquisition then apply a model inversion to recover the original image [4]. It has been also addressed by the use of special equipment (eg: laser range-gated, polarization) or the use of multiple input images [5], [6]. Although the restoration techniques mentioned above improve the contrast of the images, these methods require many unknown parameters that are difficult to precisely estimate. In addition, methods using special equipment (e.g laser range-gated) are expensive and complicated to implement. Unlike restoration, there are many methods of quality improvement which are not based on any model. They use qualitative and subjective criteria to enhance image and correct colors [7],[8],[9],[10]. Despite the simplicity and the multitude of these methods, their efficiency

- This is an Open Access article distributed under the terms of the Creative Commons Attribution-Noncommercial 4.0 Unported License, permitting all non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

© 2018 Published by ISRES Publishing: www.isres.org

decrease as turbidity is increased. The combination of several numerical methods increases the execution time, which is undesirable for real-time processing. For this reason, we propose in this paper to combine a hardware technique of quality improvement with a software one. The first is to use a polarization technique to reduce the scattering effects on the acquired images. The second is to apply an additional processing to these images with a Dark Channel Prior (DCP) dehazing method [11]. To show the interest of this approach for the target identification, we will introduce it in the following of this paper in a complete correlation recognition scheme. This article is organized as follows: first, we present the optical model of underwater images formation. Then we present the principle of polarization and DCP methods. We expose thereafter our detection and identification scheme based on phase contrast enhancement and object identification by using a correlation technique. Finally, we present the results of the correlation applied on real tests images.

Underwater Image Formation Model

The major obstacle in the underwater images processing comes from the exponential attenuation of light with a distance, which limits the visibility distance [12]. The Jaff-McGlamery model [4], is one of the most used in the literature to model the underwater image formation. This model assumes that the underwater image I received by the camera is the sum of three components: Direct attenuation I_A , forward scatter I_F and backscatter I_B .

$$I(x) = I_A(x) + I_F(x) + I_B(x) \quad (1)$$

The direct attenuation I_A is the light reflected by object that has not been diffused through the medium and reaches the camera. The forward scatter I_F , is the light reflected by the object and is scattered by the particles in its path to the camera. Backscattering I_B is the light reflected back to the camera by the particles before reaching the object. This component is often the main cause of visibility degradation, so forward scattering can be neglected. Therefore, the three-component model described by equation (1) can be simplified to:

$$I(x) = I_A(x) + I_B(x) \quad (2)$$

Or:

$$I(x) = J(x) \cdot t(x) + A(1 - t(x)) \quad (3)$$

$I(x)$ is the received intensity at the pixel x , composed of a part of the scene radiance $J(x)$ and a part of background light A according to the transmission map $t(x)$. The transmission map describes the portion of the scene " $J(x) \cdot t(x)$ " that reaches the camera. It is often written by an exponential function associated negatively with the attenuation coefficient of the medium β (β is the sum of the absorption a and diffusion s coefficients) and the scene distance d . Such as:

$$t(x) = e^{-\beta d(x)} \quad (4)$$

Thus, a point of the scene close to the camera has a short depth on which the diffusion occurs, therefore its transmission is high. $A(1 - t(x))$ Comes from the interaction between the global airlight A and the particles in the medium according to the transmission map. As we can see, when $t(x) \rightarrow 0$, $I(x) = A$. Thus, in practice the global light A corresponds to the intensity of the hazy pixel of the image. This backscatter has the effect of reducing the contrast of the observed scene and to prevent a target detection. To address this problem, we propose a new improvement approach which we will describe in the next section.

Proposed Approach

Our proposed approach is to integrate a polarimetric imaging optical system in the underwater video camera to minimize backscatter effects when acquiring images. Additional software processing by the DCP method is then applied to remove the remaining backscatter effects in these images.

Principle of Polarization

Polarization is a useful technique that removes degradation effects in underwater vision. The behavior of polarized light in seawater has been the subject of several research [13],[14]. The study of light polarization has led to the development of active and passive polarimetric imaging systems. Passive imaging uses ambient sunlight that is usually unpolarized. Light that does not reach the object becomes partially polarized by diffusion

and can be filtered by an analyzer placed in the front of the camera [15]. However, natural light is not sufficient at great depths where active imaging is preferable. Active imaging requires artificial lighting with an adapted detection scheme [16],[17]. In a linear polarization, it has been shown that the backscattered light retains the same state of polarization whatever the distance and the diffusion regime. In a circular configuration, backscattering polarization varies with distance. Thus helicity varies [18]. Thus, imaging in a cross polarization state using linearly polarized light and in the co-polarized state using circularly polarized light better discriminates the useful signal from backscattering [19]. (Fig. 1) shows a concept diagram of the polarization filtering in a linear polarization scheme.

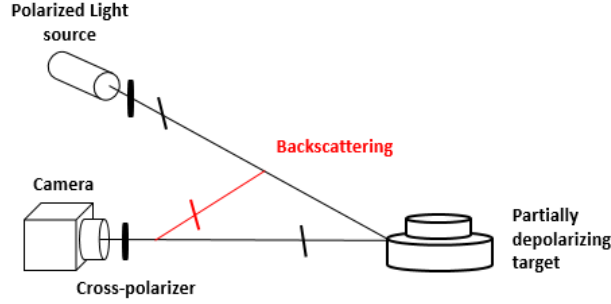


Figure 1.Principle of polarization filtering in a linear polarization scheme.

Dark Channel Prior

To a certain extent, an underwater image is similar to a hazy image, both are degraded by a turbid medium, and the captured intensity can be modeled as a sum of two components: direct attenuation and a scattered light. One of the most methods used for image dehazing is a Dark Channel Prior method. The author found that most haze free images contain some pixels whose intensity is very low in at least one of the color channels (R, G, B). This property has been verified by calculating the dark channel J^{dark} of 5000 outdoor images by [11]:

$$J^{dark}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in R, G, B} J^c(y) \right) \quad (5)$$

Where: J^c is the channel c of the image J and $\Omega(x)$ is a local window centered on the pixel x .

This observation was introduced in the model described by equation (3) to restore the scene radiance $J(x)$.

Aiming to recover $J(x)$, A is the first parameter to estimate. A^c is calculated on each channel c by the average of the 0.1% intensities of I corresponding to the brightest pixels in J^{dark} . Thus, when the global airlight A is estimated, equation (3) is normalized by A^c :

$$\frac{I^c(x)}{A^c} = \frac{J^c(x)}{A^c} t(x) + 1 - t(x) \quad (6)$$

By introducing the dark channel operator (equation (5)) into both sides of equation (6), we obtain:

$$\min_{y \in \Omega(x)} \left(\min_{c \in R, G, B} \frac{I^c(y)}{A^c} \right) = \left\{ \min_{y \in \Omega(x)} \left(\min_{c \in R, G, B} \frac{J^c(y)}{A^c} \right) \right\} t(x) + 1 - t(x) \quad (7)$$

Since $J(x)$ is the haze-free scene radiance, the dark channel of $J(x)$ is close to zero. Thus, the multiplicative term in (7) is ignored and the transmission $t(x)$ is calculated by:

$$\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left(\min_{c \in R, G, B} \frac{I^c(y)}{A^c} \right) \quad (8)$$

Once A and the transmission map $\tilde{t}(x)$ are calculated, the image $J(x)$ is restored simply from the model (equation (3)) inversion, such as:

$$J_c(x) = \frac{I_c(x) - A_c}{\max(\tilde{t}(x), \gamma)} + A_c \quad (9)$$

γ is a constant set at 0.1 to avoid out range pixel values in the restored image.

This method is known to be effective to recover the vivid colors and contrast of objects. However, the main problems are artifacts block. This is because the transmission is not always constant in a patch. To avoid this problem, the author proposes to refine the transmission map by a Soft Matting method [11] or a guided filtering [20].

Experimental Setup of Polarization

Studies on the seawater diffusion have shown that milk can be used to simulate the seawater diffusion regimes [21]. The skimmed milk contains mostly casein molecules with a mean diameter of between 0.04 and 0.3 nm, which mimic the Rayleigh diffusion regime. The semi-skimmed milk contains also a fat of 1 to 20 microns diameter, which allows us to place on Mie diffusion regime. Thus, for a c concentration (in %) of milk in a certain volume of water, the diffusion coefficient is estimated by $\mu_s = 1.40 c \text{ cm}^{-1}$ for a semi-skimmed milk and by $\mu_s = 0.42 c \text{ cm}^{-1}$ for a skimmed milk. For the wavelength considered here, the absorption coefficient of the milk can be ignored with respect to the diffusion coefficient. Thus, the crossing optical thickness τ_0 is defined to be the product of the attenuation coefficient μ_s and the distance d between the scene and the camera, such that $\tau_0 = \mu_s d$. This magnitude characterizes the diffusion regime (single or multiple). For a τ_0 smaller than 1, the diffusion is simple and for τ_0 greater than 1, it is a multiple.

In our experiments, we chose to work with skim milk because its diffusion regime is closer to the seawater diffusion (Rayleigh). A target "capital letter A" (Fig. 2(b)) is placed in an water tank at a distance of 34 cm from a waterproof camera [22]. The scene is illuminated by a light source on which a linear polarizer is fixed. Another rotating linear polarizer (analyzer) is placed on the front of the camera to control the received flow (Fig. 2(a)).



Figure 2. Light source and camera with polarizers. (b) The experimental setup

Referring to the theory and our previous works on different states of polarization used for underwater visibility improvement [16],[17], we suppose that the backscatter is mainly linear and in the same direction of the source light polarization. Thus, we fix the analyzer in the orthogonal state of source polarization to filter the useful signal from backscatter. Note that this assumption is effective if the target is sufficiently depolarizing, otherwise the utile signal is also filtered by the analyzer.

Fig. 3(a) shows the target image in pure water, Fig. 3(b) is obtained when 2cl of milk are dispersed in the 15L of water. The diffusion coefficient is thus estimated at ($\mu_s = 0.056 \text{ cm}^{-1}$), which corresponds to an optical thickness of ($\tau_0 = 1.96$). We notice in this image the appearance of a luminous veil that reduces the visibility of target. A visibility improvement is observed when the cross polarization is used Fig. 3(c). This result confirms the theory, the polarization of the backscattering is mainly linear and of the same direction as the incident light source.

However, the backscatter is not completely filtered by the analyzer. A substantial part of this is still present in the CLP image (Fig. 3(c)), which can prevent the target identification. Fortunately, the DCP improvement removed the remaining backscatter and enhance the contours of the target.

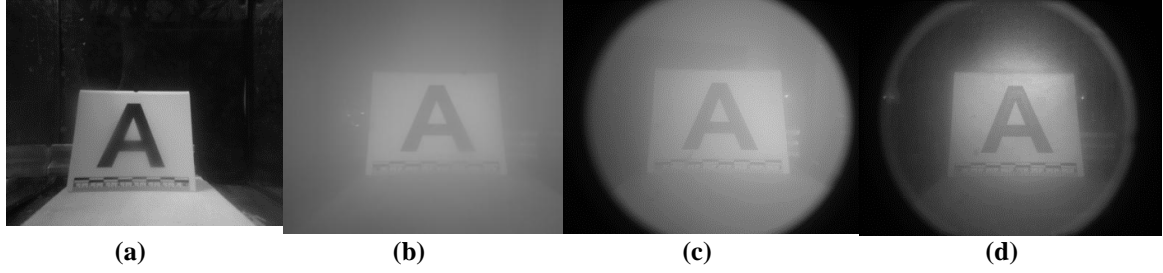


Figure 3. (a). Target in pure water. (b). Target image in turbid water ($\mu_s = 0.056 \text{ cm}^{-1}$, $\tau_0 = 1.96$) without polarization. (c) Target image in turbid water with linear cross-polarization CLP. (d) CLP image (c) improved by DCP method.

Proposed Approach for Object Identification

To see the interest of this improvement approach for underwater object identification, we will introduce it into an identification process based on correlation. The adopted object identification scheme is illustrated by the diagram of the Fig. 4:

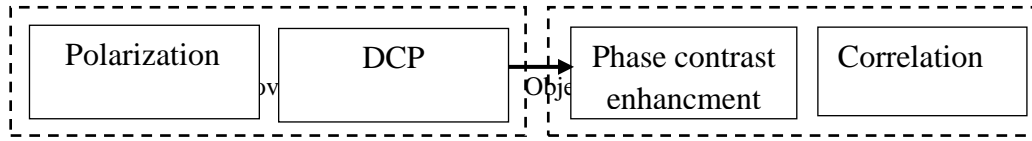


Figure 4. Proposed approach for objects identification

First we improve the quality of the image by polarization and DCP methods. Next, we identify the object by phase contrast and correlation.

Correlation

Correlation techniques have attracted considerable interest in recent years to develop automatic target recognition systems [23] [24]. The general principle of correlation is to compare an image to be analyzed with a known reference image from a learning base. This results in a correlation plane, the presence of a peak in the correlation plane indicates the similarity between the target and reference images: the larger this peak is, more the images are similar. In addition, the position of the correlation peak gives the position of the object in the target image. Fig. 5 shows the asymptotic diagram of the VLC architecture. It is based on the multiplication of the target image spectrum with a correlation filter made from the reference image. An inverse Fourier transform is then performed to have the correlation plane. Much research has been done to create robust and discriminating filters [27]. In this study, we used the Phase-only filter (POF). This filter aims to improve the correlation efficiency by using the phase of the signal that defines the contours of objects, it is written by:

$$H(u, v) = \frac{R^*(u, v)}{|R(u, v)|} = e^{-i\theta_0(u, v)} \quad (10)$$

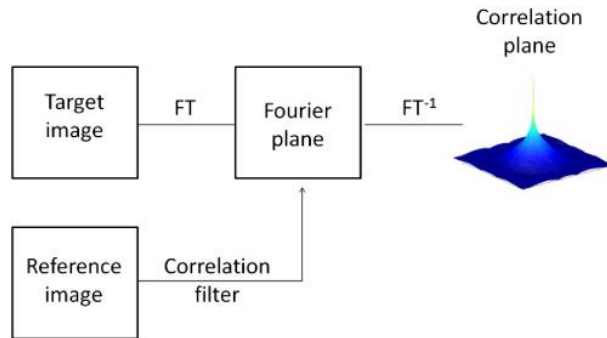


Figure 5. Synoptic diagram of VLC architecture. FT denotes the Fourier transform

Where u and v are the coordinates in the frequency plane, $R(u, v)$ is the spectrum of the reference image and $*$ denotes the conjugate complex. $e^{-i\theta_0(u, v)}$ is the phase of the signal in the Fourier domain.

Phase Contrast Enhancement

Phase contrast is an optical method used in the biological field to observe transparent cells [28]. It consists in converting the phase changes of a light wave passing through a sample into observable contrasts. Indeed, when a wave moves through a medium other than vacuum, the interaction with the medium causes changes in amplitude and phase of this wave. Amplitude changes come from light absorption and scattering phenomena, but phase changes come from interaction with objects, this effect can provide us with important information about the shape of the target. In this paper phase contrast is numerically implemented. The principle of the algorithm is to detect the contours of the objects in the image I by a gradient thresholding (Sobel for example). Then, the detected contours are enhanced by the addition of a phase φ . We thus obtain a new image (I') such as:

$$I'(x, y) = a \sin(\omega t + \varphi(x, y)) \quad (11)$$

$$\omega t(x, y) = \arcsin\left(\frac{I(x, y)}{a}\right) \quad (12)$$

The amplitude of the image signal is calculated by:

$$a = \max(I) - \min(I) \quad (13)$$

\max and \min are respectively the maximum and minimum intensities of the image I .

Thus, the phase contrast image C_p on which we apply the correlation is calculated by the difference between image I' and I .

$$C_p = I' - I \quad (14)$$

Results and Discussion

Tests carried out consist in comparing the target image " A " taken in a turbid medium by the crossed linear polarization and improved by the DCP method (Fig. 6(d)) with a reference image of the target " A " (Fig. 6(a)). Both target and reference images are obtained by applying the phase contrast algorithm respectively on the CLP image improved by DCP (Fig. 6(d)) and target in pure water (zone delimited by the red square Fig. 6 (a)). Note that the reference image (Fig. 6(b)) is then transformed into a POF filter (Equation (10)). Fig. 6 (c), shows the reference plane obtained by the correlating of the reference image Fig. 6 (b) with herself, this plan will be taken as a comparison plane of resemblance degree between target and the reference images.

In the following, we expose the results of correlation applied on the target image improved by our proposed approach. The experimental setup based on linear cross-polarization (CLP) has been detailed in section (3.1). It is interesting to observe in (Fig. 6(e)) that the phase contrast algorithm has succeeded to detect and enhance all target contours as in the reference image (Fig. (b)). This is achieved thanks to the good quality of the input image (Fig 6. (d)). Note that much less contours have been detected when we applied the phase contrast algorithm on the CLP image without the DCP additional processing. We show in Fig6. (f) the obtained correlation plan between the target (Fig. (e)) and the reference images (Fig. (b)). This plan presents a well-defined correlation peak which indicate the target identification.

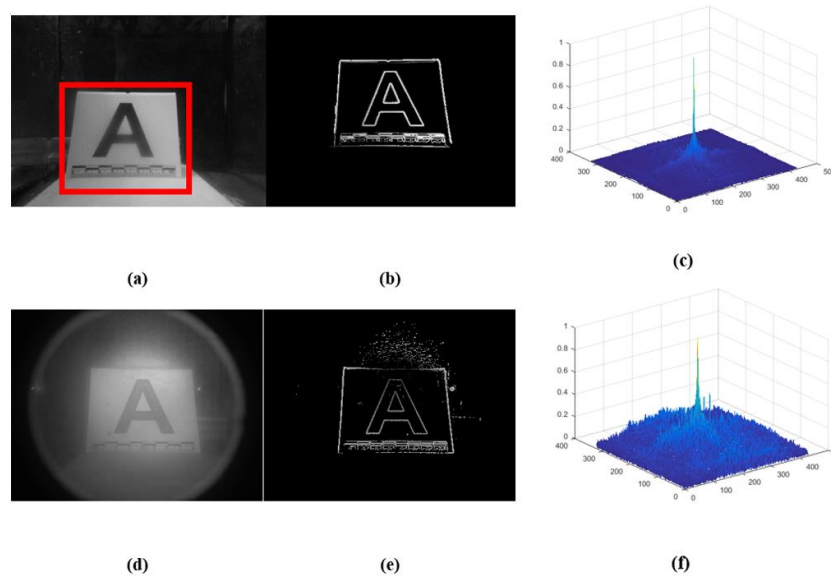


Figure 6. Correlation results. (a). Target in pure water. (b) Reference image (Phase contrast of (a)). (c). Reference correlation plan. (d) CLP image enhanced by DCP method. (e). Phase contrast of (d). Correlation plan between (e) and (b)

Conclusion

In this study, a novel approach for underwater object detection and identification is proposed. It is based on two stages. The first is the image quality improvement using the linear crossed polarization combined with the Dark Channel Prior dehazing method. This method has the advantage to eliminate backscattering effects that prevent the target detection. The second stage consist on object identification based on the VanderLaugt correlation architecture. Aiming to improve the correlation efficiency, we have used a Phase-only filter (POF). Since this filter works only on the phase of the signal (contours), we have proposed to apply a phase contrast algorithm to the input correlation images. This algorithm enhances the target by converting the phase variations (contours) to an observable intensity. Experiments have shown that this approach significantly improves target detection and identification.

References

- Sankpal, S. S., & Deshpande, S. S. (2016). A review on image enhancement and color correction techniques for underwater images. *Advances in Computational Sciences and Technology*, 9(1), 11-23.
- Schettini, R., & Corchs, S. (2010). Underwater image processing: state of the art of restoration and image enhancement methods. *EURASIP Journal on Advances in Signal Processing*, 2010(1), 746052.
- Lu, H., Li, Y., Zhang, Y., Chen, M., Serikawa, S., & Kim, H. (2017). Underwater optical image processing: a comprehensive review. *Mobile networks and applications*, 1-8.
- McGlamery, B. L. (1979, September). A computer model for underwater camera systems. In *Proc. SPIE* (Vol. 208, pp. 221-231).
- Ouyang, B., Dalgleish, F. R., Caimi, F. M., Vuorenkoski, A. K., Giddings, T. E., & Shirron, J. J. (2012, June). Image enhancement for underwater pulsed laser line scan imaging system. In *Proceedings of SPIE* (Vol. 8372, p. 83720R).
- Treibitz, T., & Schechner, Y. Y. (2009). Active polarization descattering. *IEEE transactions on pattern analysis and machine intelligence*, 31(3), 385-399.
- Garcia, R., Nicosevici, T., & Cufi, X. (2002, October). On the way to solve lighting problems in underwater imaging. In *OCEANS'02 MTS/IEEE* (Vol. 2, pp. 1018-1024). IEEE.
- Hitam, M. S., Awalludin, E. A., Yussof, W. N. J. H. W., & Bachok, Z. (2013, January). Mixture contrast limited adaptive histogram equalization for underwater image enhancement. In *Computer Applications Technology (ICCAT), 2013 International Conference on* (pp. 1-5). IEEE

- Ancuti, C., Ancuti, C. O., Haber, T., & Bekaert, P. (2012, June). Enhancing underwater images and videos by fusion. In *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on* (pp. 81-88). IEEE.
- Bazeille, S., Quidu, I., Jaulin, L., & Malkasse, J. P. (2006, October). Automatic underwater image pre-processing. In *CMM'06* (p. xx).
- He, K., Sun, J., & Tang, X. (2011). Single image haze removal using dark channel prior. *IEEE transactions on pattern analysis and machine intelligence*, 33(12), 2341-2353.
- Legris, M., Lebart, K., Fohanno, F., & Zerr, B. (2003). Les capteurs d'imagerie en robotique sous-marine: tendances actuelles et futures. *Traitement du signal*, 20(2), 137-164.
- VOSS, Kenneth J. et FRY, Edward S. Measurement of the Mueller matrix for ocean water. *Applied optics*, 1984, vol. 23, no 23, p. 4427-4439.
- Kouzoubov, A., Brennan, M. J., & Thomas, J. C. (1998). Treatment of polarization in laser remote sensing of ocean water. *Applied optics*, 37(18), 3873-3885.
- Schechner, Y. Y., & Karpel, N. (2005). Recovery of underwater visibility and structure by polarization analysis. *IEEE Journal of Oceanic Engineering*, 30(3), 570-587.
- Dubreuil, M., Delrot, P., Leonard, I., Alfalou, A., Brosseau, C., & Dogariu, A. (2013). Exploring underwater target detection by imaging polarimetry and correlation techniques. *Applied optics*, 52(5), 997-1005.
- Leonard, I., Alfalou, A., Zallat, J., Lallement, A., & Brosseau, C. (2013, October). Sensitive test for object identification based on polarization imaging and correlation. In *Frontiers in Optics* (pp. FTh3D-4). Optical Society of America.
- Brosseau, C. (1998). *Fundamentals of polarized light: a statistical optics approach*. Wiley-Interscience.
- Mullen, L., Cochenour, B., Rabinovich, W., Mahon, R., & Muth, J. (2009). Backscatter suppression for underwater modulating retroreflector links using polarization discrimination. *Applied optics*, 48(2), 328-337.
- HE, Kaiming, SUN, Jian, et TANG, Xiaou. Guided image filtering. *IEEE transactions on pattern analysis and machine intelligence*, 2013, vol. 35, no 6, p. 1397-1409.
- Piederrière, Y., Boulvert, F., Cariou, J., Le Jeune, B., Guern, Y., & Le Brun, G. (2005). Backscattered speckle size as a function of polarization: influence of particle-size and-concentration. *Optics express*, 13(13), 5030-5039.
- <http://www.sealife-cameras.com/fr/cam%C3%A9ras/dc1400-pro-vid%C3%A9o>
- Miller, P. C., & Caprari, R. S. (1999). Demonstration of improved automatic target-recognition performance by moment analysis of correlation peaks. *Applied optics*, 38(8), 1325-1331.
- Yu, F. T., & Gregory, D. A. (1996). Optical pattern recognition: architectures and techniques. *Proceedings of the IEEE*, 84(5), 733-752.
- VLC: Lugt, A. V. (1964). Signal detection by complex spatial filtering. *IEEE Transactions on information theory*, 10(2), 139-145.
- Jtc : Weaver, C. S., & Goodman, J. W. (1966). A technique for optically convolving two functions. *Applied optics*, 5(7), 1248-1249.
- Alfalou, A., & Brosseau, C. (2010). Understanding correlation techniques for face recognition: from basics to applications. In *Face Recognition*. InTech.
- Yelleswarapu, C. S., Kothapalli, S. R., & Rao, D. V. G. L. N. (2008). Optical Fourier techniques for medical image processing and phase contrast imaging. *Optics communications*, 281(7), 1876-1888.

Author Information

Khadidja Ould Amer

ISEN Brest, Vision Lab, L@bISEN, 20 rue Cuirassé
Bretagne, CS 42807, 29228 Brest Cedex 2, France
Contact E-mail: khadidja.ouldamer@gmail.com

Marwa Elbouz

ISEN Brest, Vision Lab, L@bISEN, 20 rue Cuirassé
Bretagne, CS 42807, 29228 Brest Cedex 2, France

Ayman Alfalou

ISEN Brest, Vision Lab, L@bISEN, 20 rue Cuirassé
Bretagne, CS 42807, 29228 Brest Cedex 2, France
