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Underwater video enhancement using multi-camera super-resolution

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ABSTRACT

Image spatial resolution is critical in several fields such as medicine, communications or satellite, and underwater applications. While a large variety of techniques for image restoration and enhancement has been proposed in the literature, this paper focuses on a novel Super-Resolution fusion algorithm based on a Multi-Camera environment that permits to enhance the quality of underwater video sequences without significantly increasing computation. In order to compare the quality enhancement, two objective quality metrics have been used: PSNR (Peak Signal-to-Noise Ratio) and the SSIM (Structural SIMilarity) index. Results have shown that the proposed method enhances the objective quality of several underwater sequences, avoiding the appearance of undesirable artifacts, with respect to basic fusion Super-Resolution algorithms.

1. Introduction

High-resolution images can be an important performance requirement for automated pattern recognition and scene analysis. High resolution may also improve pictorial information for human interpretation. Image resolution can be defined as a measure of the sharpness of the details of an image: the higher the resolution, the more image details can be observed. The resolution of a digital image can be categorized in many different ways: pixel resolution, spatial resolution, spectral resolution, temporal resolution (when used in videos), and radiometric resolution. In this paper, the main interest is devoted to spatial resolution. A digital image is made of small picture elements called pixels and the spatial resolution refers to the significant pixel density, measured in pixels per unit area [1].

Image spatial resolution is primarily constrained by the imaging sensors or the acquisition system. A modern image sensor is typically a Charge-Coupled Device (CCD) or a Complementary Metal–Oxide–Semiconductor (CMOS) active-pixel sensor. These sensors are usually arranged in a two-dimensional array to capture image signals. The sensor size, or equivalently the number of sensor elements per unit area, determines in the first place the spatial resolution of the image to capture. While the sensors limit the spatial resolution, image details (high-frequency bands) are also constrained by the optics, due to lens blurs (associated with the sensor Point Spread Function, PSF), lens aberration effects, aperture diffractions, and optical blurring due to motion. Constructing imaging integrated circuits and optical components to capture very high-resolution images is prohibitively expensive and not practical in most real applications. Besides the cost, the resolution of a surveillance camera is also limited by the camera speed and storage capacity. In other scenarios such as satellite or underwater imaging, it is difficult to use high resolution sensors due to size constraints. Another way to address this problem is to accept the image degradations and to use signal post-processing techniques; one of these techniques is addressed in this paper and is referred to as Super-Resolution (SR) reconstruction [2].

In this paper, the approach for SR is to construct High-Resolution (HR) video sequences from several observed Low-Resolution (LR) images, thereby increasing the high-frequency components and removing the degradations inherent to LR cameras. In our approach, every LR frame is an undersampled, aliased observation of the true scene. This idea is possible only if there is subpixel motion between these low-resolution frames, and thus the ill-posed upsampling problem can be better conditioned. In the imaging process, the camera captures several LR frames, which can be considered as a downsampled version from an HR scene with subpixel shifts between each other. SR reconstruction reverses this process by aligning the LR observations to subpixel accuracy and combining them into an HR image grid (interpolation), thereby overcoming the limitation of the camera. In terms of applications, SR arises in many areas such as surveillance video, remote sensing, medical imaging, underwater environment, or lenses design [3]. In this scope, state of the art underwater image restoration and enhancement

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techniques [4,5] could be applied as a pre-processing step for a subsequent SR stage.

The proposed system is based on capturing various LR images from several sensors, attached one to one another by an $R \times S$ array. This framework is known as a Multi-Camera (MC) system [6]. Due to the cost reduction in camera sensors, using multiple sensors along with appropriate processing techniques will be a common strategy for image enhancement in future cameras [7]. For instance, in [8] a lens attachment of 8 LR low-quality side cameras arranged around a high quality lens turns a standard DSLR (Digital Single-Lens Reflex) camera and lens into a light field camera.

The paper is structured as follows: Section 2 provides a brief review of the state of the art in underwater image enhancement. Section 3 introduces the algorithm used to enhance underwater video sequences, Section 4 addresses the proposed experimental setup to evaluate the system, Section 5 analyzes the most significant results, and Section 6 provides the most relevant conclusions.

2. Underwater imaging enhancement

Model-based SR reconstruction techniques for underwater imaging have been previously studied, as in [9], where in order to improve the resolution an imaging model based on beam propagation is established and applied to image super-resolution reconstruction techniques for an underwater range-gated pulsed laser imaging system. However, in general terms there is no commonly accepted method for image quality evaluation in the literature, or in most cases the assessment is just visual. This limitation therefore also applies to underwater imaging. In [10,11], an acoustic sequence is taken as a reference, and then denoising is applied by means of simply averaging different acoustic images. In a similar way, in [11], Chen et al. carried out a quantitative evaluation through GMG (Gray Mean Grads) and LS (Laplacian Sum) proposed by Sheikh and Bovik [12] to compare evaluation metrics of single-frame reconstruction in underwater imaging. These evaluation metrics are based on interpolations: nearest, bilinear, cubic-spline and wavelet-based, or the Papoulis–Gerchberg (PG) method, proposed and studied by Papoulis [13] and Gerchberg [14]; and evaluation metrics of single-frame reconstruction such as Projection Onto Convex Set (POCS), which is also used in [15] to enhance low contrast, strong noise and image blur of underwater video images as an outset to create a new SR reconstruction and enhancement algorithm.

Some studies use the PSNR (Peak Signal to Noise Ratio) in order to compare the bilinear interpolated image with the super-resolved image using a Basic Super-Resolution (BSR) approach, based on fusion SR techniques [16]. PSNR is calculated according to the expression in (1) based on the Mean Square Error (MSE) presented in (2):

$$PSNR = 20 * \log\left(\frac{255}{\sqrt{MSE}}\right) \tag{1}$$

$$MSE = \frac{\sum_{i=1}^{P}\sum_{j=1}^{Q}\left[f(i,j) - F(i,j)\right]^2}{P * Q} \tag{2}$$

where $f(i,j)$ is the original signal at pixel (i,j), $F(i,j)$ is the reconstructed signal (interpolated or super-resolved), and $P \times Q$ is the image size. The result of PSNR is a value in decibels (dB).

On the contrary, in [17], Pezham Firoozfam uses the RMSE (Root Mean Squared Error) to compare different turbidity levels in terms of Nephelometric Turbidity Units (NTU), and the SSIM (Structural SIMilarity) index is introduced in [18]. The SSIM expression is presented in (3):

$$SSIM = \frac{\left(2xy + C_1\right)\cdot\left(2\sigma_{xy} + C_2\right)}{\left(\bar{x}^2 + \bar{y}^2 + C_1\right)\cdot\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{3}$$

where $\bar{x}$ is the mean of x, σ_x is the variance of x, σ_{xy} is the covariance between x and y, and $C_1 = (k_1L)^2$, $C_2 = (k_2L)^2$ are two variables to stabilize the division with weak denominator where L is the dynamic range of the pixel values, being $k_1 = 0.01$ and $k_2 = 0.03$ by default.

As these metrics complement each other with respect to the information they convey, it was decided to use both PSNR and SSIM as a basis for the proposed test bench. Additionally, other works to improve the quality of underwater images not related to SR have been based on image restoration and image enhancement techniques, as will be described in the following sections.

2.1. *Image restoration techniques*

The objective of these techniques is to recover the original image from the observed image, using (if available) explicit knowledge about the degradation function (the so-called Point Spread Function, PSF) and noise characteristics. This section presents the most relevant state of the art related to this approach.

In [4] a self-adjustable filter based on a simplification of the Jaffe–McGlamery model is introduced. This simplified model is appropriate for surface waters with limited light flickering, although experimental results show that this approach can be followed in a wide variety of circumstances. As an alternative, the approach proposed in [5] is based on physical characteristics, recovering information related to scene structure (distances). In this case, it is commented that the lack of image definition is not the main cause of contrast degradation and it is concluded that polarization is the main perturbation of underwater visibility.

Another underwater image restoration algorithm is presented in [19], based on an atmospheric turbulence model. This automatic algorithm does not require previous knowledge of the acquisition conditions. This method clearly improves the contrast and image definition of underwater images. In a similar way, the study introduced in [20] shows that turbidity or marine snow is an important perturbation which can strongly diminish the performance of the color restoration algorithms, so a specific Histogram Stretching Method (HSM) is proposed to increment the robustness in environments where marine snow is present.

2.2. *Image enhancement techniques*

These methods consider neither the image composition process nor the previous knowledge of the environment. Therefore, these are simpler and faster methods than other image restoration techniques.

In [21] a contrast adjustment of the RGB color space is proposed together with intensity saturation and expansion of the HIS (Hue, Saturation and Intensity) color space. The advantage of applying two different expansion models is that it helps to equilibrate color contrast, considering at the same time the problem of illumination (light flickering). Other techniques such as a median filter, together with a dark channel are proposed in [22], where color correction is also integrated before producing the final output. Contrast and color correction are also considered in [23] using quaternionic image correction.

2.3. *Underwater environment characteristics to be considered in the SR process*

After reviewing the state of the art on image restoration and image enhancement techniques, it was concluded that the main underwater environment characteristics to be considered in the SR process are the following:

- **Color loss**: the absorption of radiations composing light is selective depending on the wavelength. Considering the visible spectrum, absorption is maximal for red color and minimum for green, and especially blue. Color loss is not only quantitative, but also qualitative, as intensity changes also depend on the specific color.