COMMENTARY

A View Through the Waves

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When using the term *underwater imaging*, what is underwater? Is it the camera? Is it the imaged object, or the light source? In most studies and engineered systems, the camera, object, and light source are all submerged. However, there may be exceptions in systems designed to operate in shallow waters, where part of the setup is above the water's surface or where natural illumination is needed from above the surface. Significantly less research and development has been conducted to image objects through a "wavy" water-air interface, where either the camera or the object is underwater, *but not both*. This commentary seeks to shed more light on this emerging domain, referred to as *intermedia imaging*.

Refracted View

Being less studied, there is a lot of room for significant innovation in intermedia imaging. You may wonder why it is important to view objects through the surface. To answer this, there are both biological and engineering drivers. Some animals must take this view to survive. While being submerged, the archer fish visually detects and localizes airborne prey (flies) and shoots them down using a water jet (shown in Figure 1), where the water jet takes an airborne parabolic trajectory (Mokeichev et al., 2010).

Analogously, while being airborne, many aquatic birds visually detect and localize submerged fish and then dive for the kill. Underwater viewpoints such as these also give a defensive advantage where fish, seals, and other underwater creatures may keep their distance from perceived predators on shore. A submerged box jellyfish (Figure 2) navigates and controls its position close to shore using eyes specifically tuned to view objects on land (Garm et al., 2011). Box jellyfish have 24 eyes of four different types, including a set dedicated to survey the airborne scene.

There are various technological applications utilizing these same viewpoints. Submerged objects can more easily be viewed looking downward through the surface from airborne or spaceborne camera platforms (Schechner et al., 2011), as compared to being viewed from cameras located on the surface. This principle is exploited in airborne lidar bathymetry. Conversely, viewing upwards from a submerged camera can facilitate a *virtual periscope* where the surrounding area around a vehicle or diver can be scouted without a salient physical probe (Alterman et al., 2013a). Figure 3 provides a good example of the periscope effect. In the image, the strong random distortion changes in both space and time. Computational vision methods can be designed to operate in the presence of these distortions, as if a virtual periscope is used.

Applications such as these are well addressed when the water surface is flat, for which the optical distortion model is deterministic. However, as we are all well aware, the water's surface is usually rather wavy or uneven, which creates image distortions that are random in space and time. This strongly inhibits high definition imaging

FIGURE 1

An Archer Fish shooting a water jet in the lab (courtesy of Ohad Ben-Shahar and Ronen Segev).

FIGURE 2

A box jellyfish where the enlarged region reveals one of its upward-looking eyes (courtesy of Jan Bielecki and Anders Lydik Garm).

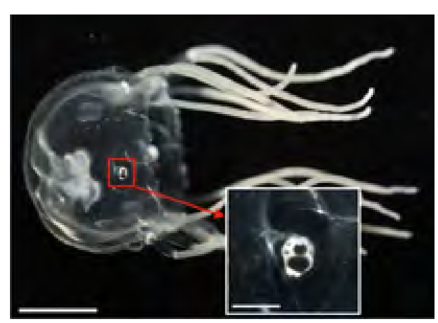


FIGURE 3

An airborne scene captured by a submerged camcorder (Alterman et al., 2013a).

through the medium as was shown in Figure 3. Consequently, applying standard deterministic imaging models and recovery methods will result in very large errors.

Rather than adhering to standard image processing approaches, there are other principles that can help. One principle incorporates the said randomness into the imaging model. This leads to *stochastic* inverse methods coupled to multiple, independent image measurements in a sequence. Methods based on this principle do not claim to achieve precise, true results but rather achieve *highly likely* results (Alterman et al., 2013b). To date, researchers have applied only a fraction of the processing and statistical tools that are available, including machine learning (Tian & Narasimhan, 2012). There is a lot of room for innovative algorithms.

Another helpful principle is that the random wavy surface can be measured. If the water surface topography is mapped while images are taken through this surface, then image distortion can be deterministically derived and inverted. In such cases, there is less need for complex algorithms. Physical measurements of the surface take the burden off the computer and transfer it to the measurement optics. Ingenious ideas have been suggested to measure water surface topography that affects images (Baglio et al., 1998; Milder et al., 2006; Schultz & Corrada-Emmanuel, 2007). Techniques include analysis of reflected sky radiance and polarization, sun-glint, laser specularities, and wave self-occlusion. These preliminary and creative methods demonstrate the richness of cues from which the wave structure can be inferred.

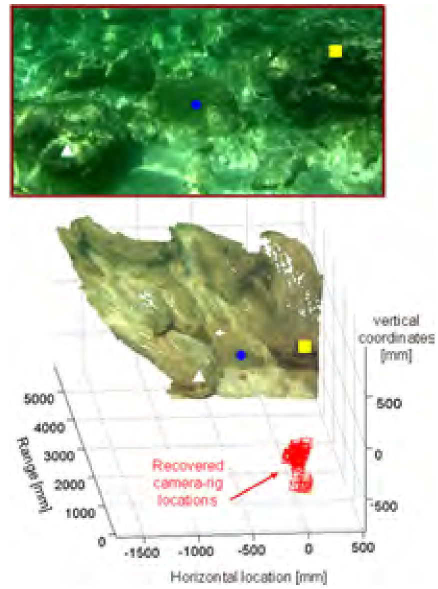
Refracted Lighting

Even if both the camera and object are submerged, the surface waves can still strongly affect images. The spatiotemporal variations of the water surface modulate sunlight refracted into the water. Natural illumination thus has a spatiotemporal random pattern, termed *sunlight flicker* or *caustic network*. The illumination modulation is so strong and fast that it often overwhelms spatial variations created by object albedo, as shown in Figure 4. This is contrary to scenes captured in air where illumination variations are typically of low frequency in space and time. It appears as if vision in the presence of caustic networks is inherently difficult; however, facts may point to the contrary. In a recent publication, Swirski and Schechner (2013) show that this effect actually eases the 3-D recovery of the underwater scene, while recovering motion of the rig carrying the camera (Figure 4).

For decades, most computer vision methods have been developed for out-of-water scenes. Hence, most computer vision methods were developed under the assumption that illumination variations consist of low frequencies, while strong changes are attributed to albedo variations. Due to sunlight flicker, these assumptions

FIGURE 4

Sunlight flicker creates a strong spatiotemporal illumination pattern on the seafloor and submerged objects (images courtesy of Yohay Swirski).



become invalid beneath the water's surface. This poses a problem when traditional, in-air computer vision methods are applied to underwater applications.

However, many shallow water marine animals have a small visual cortex and thrive in this environment. This indicates that biological vision in the presence of flickering caustics is not overwhelmingly complex if visual processing is done in way that is tuned to the flicker. Some tasks may even be made easier by this effect. To realize this, we need to bypass old notions that stem from traditional computer vision algorithms and rather think afresh on visual tasks and how caustics can be useful for them.

Consider range triangulation by stereoscopic vision, which requires determination of correspondence between image points in different locations. In air, this is usually a difficult problem. However, the spatiotemporal caustic illumination pattern very effectively establishes stereo correspondences. Thus, use of this effect has recently been termed *CauStereo* (Swirski et al., 2011). The temporal radiance variations due to flicker are unique to each object point, thus disambiguating the correspondence with very simple calculations. Hence, the random flicker actually helps to recover the 3-D scene structure like that shown in Figure 4. Moreover, being illumination invariant, the 3-D shape can be used to recognize objects or recover motion of the platform carrying the cameras (Swirski & Schechner, 2013). Furthermore, since flicker eases range recovery, it also helps in retrieving and correcting for range-dependent scattering effects.

To summarize, systems are up and running for scenarios in which both the camera and object are submerged in a fixed medium where the illumination is constant. It may be time to think more creatively for novel solutions to the difficult yet rewarding problem of random intermedium imaging.

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