Retrieval of Surface Waves Spectrum from UAV Nadir Video

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Abstract

Sea surface wave spectrum measurements are necessary for a host of basic research questions as well as for engineering and societal needs. However, most measurement techniques require great investment in infrastructure and time-intensive deployment techniques. We propose a new approach of wave measurement from standard video footage recorded by low-cost Unmanned Aerial Vehicles (UAV). We address UAV nadir imagery, which are particularly simple to obtain operationally. The method relies on the fact that optical contrast of surface gravity waves is proportional to their steepness. We present a robust methodology of regularized inversion of the optical imagery spectra, resulting in retrieval of the three-dimensional wavenumber-frequency sea surface height spectrum. The system was tested in several sea trials and in different bathymetric depths and sea state conditions. The resulting wave bulk parameters and spectral characteristics are in good agreement with collocated measurements from wave buoys and bottom-mounted acoustic sensors. Simple deployment, mobility, and flexibility in spatial coverage show a great potential of UAVs to significantly enhance the availability of wave measurements.

Introduction

Surface wave spectrum ($S_ζ$) is a critical observable for understanding air-sea interaction and its influence on climate, as well as for marine safety and marine operations planning (Ardhuin et al., 2019). Conventional in-situ wave sensors are expensive and can be difficult to deploy and retrieve. Moreover, in-situ surface wave sensors generally have sampling constraints which limit the obtainable spectral information, e.g., in most cases they do not directly measure the spatial (wavenumber) dependence of the spectrum, or do so coarsely.

Optical camera systems represent an alternative approach to retrieve surface wave spectrum, which may be more affordable and simpler to deploy than many in-situ wave sensing systems. Additionally, by observing both the temporal and spatial variability of the sea surface, optical camera systems can provide a direct measurement of the full (three-dimensional) wavenumber-frequency wave spectrum, given a methodology to deduce the surface wave state from the optical signal. Several physical principles have been exploited in order to optically estimate wave spectra. The optical brightness contrast of surface waves has been utilized to estimate wavenumber spectrum from single images taken by cameras mounted on coastal towers (Stilwell Jr., 1969; Kasevich et al., 1972; Lubard et al., 1980; Chickadel, 2007). Additionally, a qualitative proxy of wavenumber spectrum was derived from a fixed-wing-based system by (Dugan et al., 2001). Other investigators have derived surface wave spectra based on reflected light polarization changes (Zappa et al., 2008; Laxague et al., 2018; Ginio et al., 2023), or based on stereo imaging (e.g., (Benetazzo et al., 2012)).

Here we demonstrate the feasibility of applying an optically-based wave spectrum estimation technique from a hovering Unmanned Aerial Vehicle (UAV, aka drone).

While the term Unmanned Aerial System (UAS) is gaining in popularity, we use the term UAV to emphasize that we use a consumer grade product rather than a system designed towards the present purpose.
imagery. We propose a different approach, which obtains the full 3D spectrum, and our validation includes in-situ observations of the frequency spectrum. Fourier spectrum of UAV videos has been successfully used for measurement of surface current velocity, based on the measured Doppler shifts of the spectrum (Strößer et al., 2017; Yurovsky et al., 2022; Dolcetti et al., 2022). However, the current velocity inversion was based on the video (gray level) spectrum. A processing algorithm was not provided to convert the video gray level spectrum to sea surface height wave spectrum.

UAV-based wave measurements can provide multiple advantages over current commonly used approaches, including in cost, flexibility of deployment location, and ease of deployment, allowing the collection of wave data over a wide range of temporal and spatial scales. The technique proposed here is based on wave brightness contrast, which requires less elaborate measurement systems than the other mentioned optical techniques. For example, stereo measurement requires multiple and synchronized cameras, while polarimetric imaging requires polarimetric cameras. The use of the simplest optical technique increases the technical and material accessibility of the method, which can and is applied here using cheap (currently with a price of several 1000$\) consumer-grade quad-copter UAVs. Another break from previous wave spectra from previous optical brightness based wave measurements is the full use of time-sequential video data (rather than single images) and subsequent use of spatio-temporal spectrum to infer wave directionality (rather than just axis of propagation which can be deduced from single images), to infer (and correct for, if desired) Doppler-shift by ambient currents, and to reduce bias from non-wave processes.

Previous optical brightness based investigations of wave spectra (Stilwell Jr, 1969; Kasevich et al., 1972; Lubard et al., 1980; Chickadel, 2007) have focused on slant (tower-based) camera geometries. We focus on nadir UAV imagery, at which the polarization-dependence of reflectivity can be neglected, simplifying the observational procedure and the analysis. Off-nadir imagery additionally increases the image-rectification errors, which may be problematic due to consumer-grade UAVs angular position keeping accuracy. Finally, recording imagery in nadir eliminates two degrees of freedom (pitch and roll), which can simplify UAV operations and their data processing. The simplification can be a significant advantage in campaigns involving multiple platforms for example. A new and robust methodology for conversion of video data to wave spectra under these conditions is introduced, and wave spectra are obtained and validated over a larger frequency range than was possible in previous investigations.

The paper is organized as follows. In section we present our methodology for inferring the sea surface wave spectrum from UAV video spectrum. In section we present sea trials in which we measured surface wave spectra via UAV video footage processed using the developed methodology, and compared them with in-situ measurements. The results of the sea trials are presented and analyzed in section. Challenges and prospects of the new approach are discussed in section, and a summary is provided in section.
Methodology

Figure 1: Schematic of reflection optics. A camera system is located above the sea (on an hovering UAV), looking downwards. At any specified angle of observation within the camera field of view, the light reflected from the sea surface towards the camera (ray #3; light rays shown in blue) emanates from skylight arriving downwards from an angle dependent on the sea surface slope, e.g. ray #2 for a hypothetical flat sea surface (dashed black line) vs ray #1 for the hypothetical undulating surface shown (solid black line).

Transformation from Video Spectrum to Wave Spectrum

The wave spectrum measurement proposed here is based on analysis of sea surface videos recorded from a stationary (hovering) UAV. The intensity distribution $I(x,y,t)$ of skylight reflected at time $t$ from the sea surface $(x,y)$ position towards the camera can be written to first order in a Taylor expansion in the surface slope as:

$$I(x,y,t) = I_0(x,y) + \nabla_s I_0(x,y) \cdot s(x,y,t),$$

(1)

where $I_0(x,y)$ is the hypothetical image intensity in the absence of waves, but with identical sky illumination conditions (hereafter referred to as reference skylight brightness); and $s(x,y,t)$ is the sea surface slope vector distribution. We estimate $I_0$ from the video data (section ). The expression $\nabla_s I_0(x,y)$ is the vector derivative of the reference skylight brightness with respect to the sea surface slope. The dependence of $I(x,y,t)$ on the (Fresnel) reflectively coefficients is neglected here, as detailed in the discussion section. From equation 1,

$$I(\theta,t) = I_0(\theta) + \nabla_\theta I_0(\theta) \cdot s(\theta,t),$$

(2)

where $\theta = (\theta_x, \theta_y)$, the latter being the field of view (FOV) angles in each camera axis, corresponding to location $(x,y)$ in equation 1. Denote the gradient with respect to view angle as $\nabla_\theta$. Given that a unit change in surface slope changes the reflection angle of a light ray by approximately two units\(^2\), it follows that $\nabla_s I_0(\theta) \approx 2\nabla_\theta I_0(\theta)$. Therefore, using $s = \nabla \zeta$, with $\zeta$ being sea surface height (and the nabla without subscript denoting the standard Cartesian horizontal coordinate gradient),

$$I(\theta,t) - I_0(\theta) = (2\nabla_\theta I_0(\theta)) \cdot \nabla \zeta(\theta,t).$$

\(^2\)That is exactly true in one dimensional geometry, but it is (approximately) true for two dimensional Cartesian angles $(\theta_x, \theta_y)$ only for small angles.
If $\nabla_\theta I_0$ is approximately a vector constant (which we will denote with $\nabla_\theta I_{0P}$), i.e. $I_{0P}$ is linear in $\theta$, then the Fourier transform $\mathcal{F}$ of the last equation along the $x - y - t$ coordinates is

$$\mathcal{F} [I - I_0] (k, \omega) = (2\nabla_\theta I_{0P}(\theta)) \cdot k \mathcal{F} [\zeta] (k, \omega),$$

(4)

where the vector wavenumber is denoted by $k$ and the temporal frequency is denoted by $\omega$. By multiplying equation 4 with its complex conjugate the following relation is obtained between the optical intensity spectrum $S_I$ (which we define by $|\mathcal{F} [I - I_0]|^2$) and the sea surface height (SSH) spectrum $S_\zeta = |\mathcal{F} [\zeta]|^2$:

$$S_I(k, \omega) = (2\nabla_\theta I_{0P} \cdot k)^2 S_\zeta(k, \omega).$$

(5)

In order to compute the SSH spectrum from the video spectrum, the last relation can in principle be simply inverted:

$$S_\zeta(k, \omega) = \frac{1}{4|\nabla_\theta I_{0P}|^2 |k|^2 \cos^2(\phi_k)} S_I(k, \omega).$$

(6)

Hereafter $\phi_k$ is the angle between the vectors $\nabla_\theta I_{0P}$ and $k$. The usefulness of this formula is that the SSH spectrum is completely determined by the right hand side, i.e., by the video data. That includes the video spectrum $S_I$ as well as the reference skylight brightness $I_0$, which is obtained by a proper smoothing and averaging of the video (section ). In this manner, there is no need to appeal to theoretical models of skylight illumination distribution (e.g., (Chapman, 1981)), with uncertain relation to field conditions.

There are several remaining issues with the derived SSH spectrum. Firstly, deviations from uniformity of the mean sky brightness gradient need to be addressed. Secondly, the expression (6) contains an artifact of being unbounded in the direction perpendicular to the skylight gradient. To address these two issues, we introduce empirical modifications of equation (6) in section . A third issue, addressed in section , is that the SSH spectrum may be Doppler-shifted by ambient currents, and in general contains combinations of wavenumber and frequency which are not directly related to surface gravity waves and hence may be regarded as noise.
Background Optical Brightness Estimate

The inference of the wave spectrum by the methodology described in section requires an estimation of the reference skylight brightness \( I_0 \) or \( I_{0P} \) and its gradient \( \nabla_\theta I_0P \). Rather than define \( I_0 \) based on empirical optical models of skylight brightness (e.g., (Chapman & Irani, 1981)), we estimate \( I_0 \) from the video itself. Since we assume reflectivity is uniform (see discussion in section ), the skylight brightness (in camera digital units) at each elevation and azimuth angles is equal to the camera signal that would be received from the the same azimuth and from the complementary elevation angle in reflection from a hypothetical flat sea surface, i.e., in the absence of waves. The signal in the hypothetical absence of waves can in principle be approximated by a time-average of the analyzed video data, under the assumption that statistically the waves are close to symmetrical around their crests. In practice, we use a time-median instead of a time average since it too can remove a wave signal, while being more robust to large statistical fluctuations.

We also apply spatial smoothing to remove bright surface features such as sun glitter, floating material, e.g., foam from breaking waves, and objects (incidental, e.g., sea birds, or intentionally introduced, e.g., oceanographic equipment such as drifters). The smoothing is affected by a moving median operation in each spatial axis. The reference skylight brightness \( I_0 \) is therefore estimated as follows:

\[
I_0(x, y) = \text{median}_t[\text{movmedian}_y[\text{movmedian}_x[I(x, y, t)]]],
\]

(7)

where \( \text{median}_t \) signifies the median operation across the entire analyzed time interval. “movmedian_\text{c}” signifies a median sliding window operation across spatial axis \( \text{c} \). Here we used a sliding window size of 6°, over which we do expect skylight to be near-uniform.

Following the operation in equation 7, we additionally smooth \( I_0(x, y) \) by convolution using a Gaussian kernel of standard deviation=3°. The purpose of the Gaussian smoothing here is to replace integer-valued spatial image differences with non-integer values, to improve the smoothness and robustness of derivatives calculated from the reference image (see below, e.g., in equation 9).

After \( I_0 \) is estimated, it is used both directly - removed from \( I \) in the calculation of \( S_I \) (equation 4) - and in calculation of the optical intensity gradient \( \nabla_\theta I_0(\theta) \) (equation 1). The gradient is calculated by estimating a best-fit plane \( I_{0P}(\theta) \) to \( I_0(\theta) \):

\[
I_0(\theta_x, \theta_y) = I_{0P} + \Delta = p_0 + p_{1x}\theta_x + p_{1y}\theta_y + \Delta(\theta_x, \theta_y).
\]

(8)

The plane fit residual is denoted by \( \Delta \). The fit plane coefficients \( (p_{1x} \text{ and } p_{1y}) \) then provide the desired gradient. The quality of the plane fit is addressed in sections and .
Non-uniform skylight gradient fraction

In the above we assumed that to a good approximation the skylight brightness gradient is uniform, i.e., that gradients in the non-linear skylight brightness residual $\Delta$ are negligible relative to gradients in $I_{0P}$. That need not be the case in reality. We therefore suggest the following empirical extension of the spectral estimate to take into account the residual:

$$S_\zeta(k,\omega) = \frac{S_I(k,\omega)}{4|k|^2 \left[ |\nabla I_{0P}|^2 \cos^2(\phi_k) + |\nabla \Delta|^2 \right]},$$

(9)

where an overline denotes a spatial average over the field of view (FOV). The necessity of this empirical modification is demonstrated in section , based on our sea trials.

The modification in equation 9 simultaneously resolves a second potential difficulty: the spectrum expression in equation 6 is unbounded for waves traveling perpendicular to the sky brightness gradient (i.e., for $\phi_k \rightarrow 90^\circ$). The residual term in equation 9 regularizes the expression, limiting the spectrum to finite values.

While the regularization eliminates the singularity, nonphysically large spectrum values are still possible near $\phi_k = 90^\circ$, in case that $|\nabla I_{0P}|$ is much larger than $|\nabla \Delta|$. Thus, noise in directions near $\phi_k = 90^\circ$ can be amplified by orders of magnitude and can cause severe artifacts. For example $1/\cos^2(\phi_k)=10$ (100) for $\phi_k = 72^\circ$ ($84^\circ$). To ensure that the regularization is effective enough in this regard, we set a minimum relative value (hereafter $B$) for the residual term in the spectrum expression:

$$S_\zeta(k,\omega) = \frac{S_I(k,\omega)}{4|k|^2 \left[ |\nabla I_{0P}|^2 \cos^2(\phi_k) + M \right]},$$

(10)
\[ M = \begin{cases} 
B |\nabla_\theta I_0 P|^2, & \text{if } |\nabla_\theta \Delta|^2 < B |\nabla_\theta I_0 P|^2 \\
|\nabla_\theta \Delta|^2, & \text{otherwise}
\end{cases} \]

We choose a value of \( B = 0.2 \), which results in a full-width half max (FWHM) angular spread of 55 degrees. That is a reasonable value to use since similar or higher FWHM directional spreads are typical in wave observations (Mitsuyasu et al., 1975; Donelan et al., 1985; Banner, 1990; Young, 1999).

**Dimensionality Reduction, Noise Suppression, and Doppler-Shift Correction**

So far we have derived an estimate of the three-dimensional wavenumber-frequency spectrum of sea surface height spectrum (a three-dimensional visualization of the spectrum is shown in figure 3). Since wavenumbers and frequencies are related through the linear dispersion relation, it can also be useful to reduce the directional wavenumber-frequency spectrum \( S_\zeta(k, \omega) \) to a directional wavenumber-only \( S_w(k) \) spectrum (or to a directional frequency spectrum). The succinct representation is advantageous in analysis as well as visual examination of the spectrum. Note also that a wavenumber spectrum can be derived from single images rather than a video sequence, but the present (latter) approach also provides directionality, as well as an additional filter to remove noise (fluctuations other than linear waves) from the wavenumber spectrum.

The linear wave dispersion relation \( \Omega(k) \) can be written as the relation between the absolute (i.e., Doppler-shifted) linear wave frequency \( \Omega \) and wavenumbers \( k \),

\[
(\Omega - k \cdot V)^2 = g k \tanh (kH),
\]

where \( g \) is the gravitational acceleration constant, \( H \) is the bathymetric depth, and \( V \) is the ambient current (i.e., a current which is approximately constant over the spatio-temporal scales of the waves being considered). Surface tension can be neglected in the dispersion relation for wavelengths longer than several cm, as studied here.

We remove the redundant frequency dimension from the spectrum by integrating the spectrum over a frequency interval \( (\Delta \omega) \) centered around the dispersion relation at every wavenumber. The interval width we have used is 0.5 radian per second. The Doppler shift by the ambient current \( V \) can be deduced from the UAV video by the optimization method of (Streßer et al., 2017), via their matlab code, CopterCurrents, or it may be obtained from an in-situ current sensor for example. The collapsed (linear dispersion relation) directional wavenumber spectrum is then given by:

\[
S_w(k) = \int_{\Omega(k, V) - \Delta \omega/2}^{\Omega(k, V) + \Delta \omega/2} S_\zeta(k, \omega) d\omega.
\]
A directional frequency spectrum\(^3\), \(S_w(\hat{k}, \omega)\), can be derived similarly:

\[
S_w(\hat{k}, \omega) = \int \! \! \int \! \! S_\zeta(\hat{k}, k, \omega) \delta(\omega - \Omega(k, V)) dk.
\]

(14)

Here \(\hat{k}\) denotes a unit vector in the direction of the wavenumber vector, and we have written the dependency of \(S_\zeta\) on the wavenumber vector \(k\) as a double dependence on the wavenumber magnitude \(k\) and the wavenumber direction \(\hat{k}\). The \(\delta(x)\) symbol denotes the Dirac delta function. In the numerical computation of this integral we define \(\delta(\omega)\) as having value of one \((1)\) for \(|\omega| \leq \Delta\omega/2\), and a value of zero otherwise.

Figure 3: Three-dimensional view of the sea surface height spectrum, i.e., equation 9. Two planar sections of the spectrum \(S_\zeta(k, \omega)\) are shown: the \(k_x - k_y\) plane (where \(k_x\) and \(k_y\) are the wavenumber components in the directions \(x\) and \(y\), respectively) and the \(k_x - \omega\) plane.

**Implementation**

The developed methodology is implemented as an expansion of the CopterCurrents open-source matlab package. CopterCurrents is used (Streßer et al., 2017) as a technical basis for handling the UAV video data,

\(^3\)For simplicity, we use the same symbol \((S_w)\) for the wavenumber spectrum and for the frequency spectrum, and differentiate between them based on the arguments.
georectification, calculating video Fourier spectra\(^4\), and (see section \()\) for Doppler shift inference. Camera calibration was also conducted based on the same matlab tools recommended in the CopterCurrents manual\(^3\).

We divide the field of view to square (in terms of FOV angles) windows, and estimate the reference skylight brightness and the wave spectrum (separately) in each window. The square shape is chosen for computational ease and for avoiding computational bias in the azimuthal distribution of waves. To that end, the spectrum is only estimated for wavelengths \(\lambda \leq \lambda_{\text{max}}\), where \(\lambda_{\text{max}}\) can be chosen to be either equal to or smaller than the window side length \((L)\). We have used \(\lambda_{\text{max}} = L/2\) in all cases presented in section \. We apply separately in each window the computations outlined in the previous subsections. To minimize spectral leakage artifacts in the wave spectrum, we detrend the video data in each spatial axis, and apply Hann windows in each spatial and temporal dimension prior to applying Fourier transforms. We compensate for the variance lost in the three windowing operations by multiplying the video data by \((8/3)^3\). We maintain an area overlap of 50\% between adjacent windows to maximize the degrees of freedom, in accordance with best practices (Thomson & Emery, 2014).

The spectral estimates from different analysis windows are averaged to produce the final spectrum estimate. We assume that the wave field is statistically uniform within the field of view. If there is a reason to assume otherwise (e.g. in transitional regions near shore or near fronts), the spectra should only be averaged across FOV windows where the wave regime is near uniform. We apply a weighted average, where the weights are metrics of the quality of the plane (linear) fit of the background brightness (section \). Specifically, we use the coefficient of determination \((R^2)\) value, defined as follows (where an overline denotes a FOV-average):

\[
R^2 = 1 - \frac{(\overline{I}_0 - \overline{I}_0 P)^2}{(\overline{I}_0 - \overline{I}_0)^2}.
\]

(15)

\(R^2\) may be interpreted as the fraction of \(I_0(\theta)\) variance explained by the plane fit \(I_0 P\). Thus the spectrum is finally estimated via

\[
< S_\zeta > = \frac{\Sigma_i R^2_i S_{\zeta,i}}{\Sigma_i R^2_i},
\]

(16)

where spectral estimates from different windows are marked by different \(i\) indices. The \(R^2\) weighted-average is a sensible definition for the mean spectrum since the transformation from video to wave spectra relies on the approximation of a uniform reference brightness gradient, and the \(R^2\) value is a measure of the quality of this approximation. Note that to increase statistical robustness one can add to the weighted average spectra calculated from multiple temporal segments of the video.
### Table 1: Sea trials conditions. Reference wave conditions (section ) are based on the validation sensors or (in first row) on reanalysis data. Note that the wave parameters given here are calculated based on the full spectral range of each validation sensor, including lower frequencies than measured by the UAV. These values are for reference regarding general conditions, while the actual validation (section ) is based on data subsetting to the overlapping frequency range.

<table>
<thead>
<tr>
<th>Date</th>
<th>Hour</th>
<th>Location</th>
<th>Longitude °E</th>
<th>Latitude °N</th>
<th>Bathymetric Depth</th>
<th>Wind Speed</th>
<th>Wind Direction</th>
<th>SWH</th>
<th>$T_p$</th>
<th>$\Theta_p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>08-Feb-2022</td>
<td>10:45</td>
<td>Offshore</td>
<td>34.411071</td>
<td>31.819678</td>
<td>125 m</td>
<td>3 m/s</td>
<td>255°</td>
<td>0.47 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20-Feb-2022</td>
<td>07:30</td>
<td>Tzuk Beach</td>
<td>34.774361</td>
<td>32.134667</td>
<td>15 m</td>
<td>3 m/s</td>
<td>170°</td>
<td>1.1 m</td>
<td>8.5 s</td>
<td>305°</td>
</tr>
<tr>
<td>04-Mar-2022</td>
<td>10:15</td>
<td>Tzuk Beach</td>
<td>34.774361</td>
<td>32.134667</td>
<td>15 m</td>
<td>7.5 m/s</td>
<td>235°</td>
<td>2.6 m</td>
<td>11.1 s</td>
<td>297°</td>
</tr>
<tr>
<td>22-Jun-2023</td>
<td>05:55</td>
<td>Offshore</td>
<td>34.5006</td>
<td>32.2162</td>
<td>590 m</td>
<td>2.5 m/s</td>
<td>225°</td>
<td>0.62 m</td>
<td>5.7 s</td>
<td>289°</td>
</tr>
</tbody>
</table>

### Table 2: UAV configuration details.

<table>
<thead>
<tr>
<th>Date</th>
<th>UAV Model</th>
<th>Video Format</th>
<th>FOV</th>
<th>Altitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>08-Feb-2022</td>
<td>Mavic 2 Zoom</td>
<td>3840×2160</td>
<td>76°</td>
<td>158 m</td>
</tr>
<tr>
<td>20-Feb-2022</td>
<td>Phantom 4 Pro</td>
<td>4096x2160</td>
<td>90°</td>
<td>100 m</td>
</tr>
<tr>
<td>04-Mar-2022</td>
<td>Phantom 4 Pro</td>
<td>3840×2160</td>
<td>90°</td>
<td>101 m</td>
</tr>
<tr>
<td>22-Jun-2023</td>
<td>Phantom 4 Pro</td>
<td>4096x2160</td>
<td>90°</td>
<td>250 m</td>
</tr>
</tbody>
</table>

## Sea Trials and Validation

### Sea Trials

We conducted four separate sea trials, off the Israeli coast in the Eastern Mediterranean Sea. Sea trial details and reference conditions, including wave and wind conditions, are detailed in table 1. Blank entries correspond to data which is not available at the time of this writing. Wind data for the Tzuk Beach trials is based on The Israeli Meteorological Service (IMS) Tel Aviv station records. The 08-Feb-2020 trial wind data is based on the IMS Ashkelon (coastal) station. The 22-Jun-2023 offshore trial wind data is based on a measurement onboard the research vessel using a hand-held meteorological sensor. The sky were clear to ≈25% cloudy during all the sea trials.

Two sea trials were conducted 1 km offshore of Tzuk Beach in central Israel during 20-Feb-2022 and 04-Mar-2022. The UAV was flown from the beach in these two coastal trials. An upward-looking Acoustic Doppler Current Profiler (ADCP, model Sentinel from RDI) was placed in a bottom mount located about 1 km offshore, and the UAV footage was recorded above its position. The ADCP recorded data at 2 Hz in 17 minute intervals, and its wave analysis was done based on acoustic surface tracking and on the horizontal velocity measurements near the surface, i.e. the “SUV method” (Pedersen et al., 2005).

Two additional sea trials were conducted several tens of km from the shoreline. In both cases, the UAV was operated from a research vessel, the Mediterranean Explorer, operated by the non-profit environmental organization EcoOcean. The first offshore sea trial was conducted at 08-Feb-2022, about 20 km offshore of Ashkelon, Israel. For validation, in-situ surface wave and wind data were retrieved (https://isramar.ocean.org.il/isramar2009/) from a wave buoy positioned ≈15 km south-south-west of the UAV. The second offshore sea trial was conducted at 22-June-2023, about 30 km offshore of Herzliya, Israel. For validation, a freely-drifting wave buoy (Spotter model from Sofar Ocean, (Raghukumar et al., 2019)) was

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4 We have modified the Fourier transform normalization choice in the CopterCurrents code so that its integral equals the video graylevel spatio-temporal variance.

5 https://github.com/RubenCarrascoAlvarez/CopterCurrents
deployed and was within ≈1 km from the UAV. In the latter case, buoy data was analyzed and compared with the UAV in two separate time windows: 05:27-05:57, and 06:30-06:38.

We used two types of unmodified consumer-grade UAVs. The UAV model in use in the 08-Feb-2022 cruise was DJI Mavic 2 Zoom. The camera was operated in minimal zoom (24 mm). In the other three sea trials the UAV model in use was a DJI Phantom Pro 4. Unlike the Mavic Zoom model, the Phantom model camera did not have a zoom lens. The Phantom UAV has the desirable property in the present context that pitch, roll, and yaw of the camera, as well as UAV height\(^6\) are automatically recorded by the UAV into the video metadata. These metadata can be read by open source software packages (e.g. MediaInfo, https://mediaarea.net/en/MediaInfo), facilitating the imagery georectification. In the Mavic UAV, the angles metadata were not recorded (height was), but care was taken to record videos in nadir, and in a fixed azimuthal direction which was noted and used in the georectification.

In all sea trials, as required with the present methodology, the UAV was hovering (approximately) statically i.e. in position-keeping mode while recording the video data with its camera pointed directly downwards (i.e. in nadir). UAV camera video was recorded at a frame rate of 30 frames per second. Other configuration details are given in table 2. The altitude given in the table refers to the UAV height above the sea surface during the video recording. The imagery diagonal field of view in each case was 76-90° (table 2). The surface footprint increases with the FOV and with the UAV hovering height, which may be limited by local regulations (see section ).

In all cases, the data was analyzed independently in multiple FOV sub-windows (see section ) with a surface footprint side length of 80 m or larger. In the June 2023 experiment 200 m windows were possible due to higher flight altitude. We analyze the spectrum in wavelengths up to half the spatial window width. In all cases, we analyzed 24 second segments of UAV videos. The 2D frequency or wavenumber spectra from \(N_t\) (=3–4) temporal video segments, and \(N_x\) partial windows were averaged before calculation of any bulk parameters, 1D spectra, or comparison with in-situ sensors. The interval between time segments was 12 seconds (i.e., 50% overlap, see section ) in the 22-Jun-2023 sea trial. In the earlier sea trials more data was recorded, and the interval between time segments was taken as close as possible to 2.5 minutes (which was the shortest approximately consistently available interval) within the relevant in-situ observation interval to minimize sampling bias. The maximal number of spatial windows with 50% overlap (section ) was applied in each case, resulting in \(N_x = 3-8\). One exception is that for the 22-Jun-2023 05:55 data, we only used one spatial window (\(N_x=1\)) since the other two thirds of the FOV had very low optical contrast, and a substantial spatial noise (of an unidentified source) was visible in the video in this low-contrast FOV sub-area. The values of \(N_t\) and \(N_x\) per analyzed video footage are given in table 3.

Wave Reanalysis

We use information from the Mediterranean Sea wave reanalysis product MEDSEA_MULTIYEAR_WAV_006_012 (Zacharioudaki et al., 2020) for part of the validation of UAV-derived wave properties. The reanalysis is based on the WAM Cycle 4.6.2 wave model, at a horizontal resolution of 1/24°. The spectrum frequency is discretized with 24 values in the range 0.04177–0.8018 Hz, and 24 directions (i.e., 15° width of spectrum direction bins).

Evaluation metrics

We briefly describe the mathematical definitions of quantities used in the method validation and evaluation against in-situ measurements, including bulk wave properties and reduced spectra (e.g., frequency spectrum

\(^6\)Height above the takeoff point is recorded, which we convert to height above sea level.
or wavenumber-magnitude spectrum). The Significant Wave Height parameter is computed via:

\[ SWH = 4\sqrt{\int S_w(k)d^2k}. \]

(17)

The (vector) wavenumber probability density function of surface waves is just the surface-wave wavenumber spectrum \( S_w \) normalized by its 2D integral. Hence the average \( \langle a \rangle \) of any wave quantity \( a \) (e.g., wave period, direction, etc.) is a "bulk property" that can be calculated from the wavenumber spectrum by weighted-averaging as follows,

\[ \langle a \rangle = \frac{\int S_w(k)a(k)d^2k}{\int S_w(k)d^2k}. \]

(18)

The mean wave "to" direction is defined as \( \hat{k} \), the weighted-average value of the unit (marked by hat symbol) wavenumber vector \( k \). We display everywhere in this paper the opposite direction, i.e., the wave "from" direction (hereafter \( \Theta \)).

Directional spread is defined as follows (Jammalamadaka et al., 2001; Kuik et al., 1988):

\[ \sigma = \frac{180^\circ}{\pi} \sqrt{2 \left[ 1 - \left( (\cos(\theta_k))^2 + (\sin(\theta_k))^2 \right) \right]}, \]

(19)

where \( \theta_k \) is the polar angle of wavenumber \( k \).

For deriving directional parameters from wave buoys (mean direction \( \Theta_b \) and directional spread \( \sigma_b \)), we follow (Kuik et al., 1988) and (Lancaster et al., 2021) in computing them directly from the directional Fourier coefficients:

\[ \tilde{\Theta}_b = \tan^{-1}(\frac{b_1}{a_1}), \]

(20)

\[ \sigma_b = \frac{180^\circ}{\pi} \sqrt{2 \left[ 1 - \left( \frac{\sigma_1^2(\omega) + \sigma_2^2(\omega)}{} \right) \right]}, \]

(21)

The wave "to" direction \( \Theta_b \) is then the opposite direction to \( \tilde{\Theta}_b \). Here \( a_i \) and \( b_i \) are \( i^{th} \) cosine and sine coefficients in a Fourier expansion of the directional dependence of the spectrum\(^7\). The averaging operation

\(^7\)Wave buoy measurements allow to estimate only the first five directional Fourier coefficients \( a_0, a_1, a_2, b_1, \) and \( b_2 \).
(overline symbol) in equations 20-21 are defined in a similar way to equation 18, except that the buoy frequency spectrum is used for the weighting function.

We also compare the non-directional frequency spectrum $S_w(\omega)$ directly with the same spectrum as measured by an ADCP or wave buoy. For completeness, the transformation from directional frequency spectrum to non-directional frequency spectrum is defined as follows,

$$S_w(\omega) = \int S_w(\hat{k}, \omega) d\hat{k}.$$  \hspace{1cm} (22)

The following standard metric of a mean wave period is computed via moments of the frequency spectrum:

$$T_{m2} = \left[ \frac{1}{\bar{\omega}^2} \right]^{-\frac{1}{2}}.$$  \hspace{1cm} (23)

Our UAV-derived spectra reach higher frequencies than available from the validation sensors used in our sea trials, i.e., ADCPs and wave buoys, which are commonly limited to wave frequencies lower than roughly 1 Hz. These instruments are also limited by noise near this frequency, e.g. above about 0.25 Hz for ADCPs. We therefore define a parameter, “HFRatio”, to quantify the ratio of in-situ ($S_w(\omega)$) and UAV-derived ($S_i(\omega)$) spectral values in the high frequencies (\$0.25 \text{ Hz}$),
Figure 4: Verification of the importance of including the non-linear reference brightness variability in the conversion of graylevel spectrum to SSH wave spectrum. The ratio of non-linear variability to linear gradient magnitude, $\frac{\left| \nabla \theta \Delta \right|^2}{\left| \nabla \theta I_0 \right|^2}$, is plotted as a function of the linear goodness of fit parameter $R^2$. Each data point corresponds to one spatial analysis window in one of the sea trial dates and times (see legend).

Results

Reference Brightness Linearity

In section we devised an empirical “fix” to the wave spectrum inversion process to account for non-linear sky brightness distribution. Examination of actual reference brightness gradient values in our sea trials (figure 4) confirms that the ratio of the non-linear (“residual”) to the linear reference brightness distribution terms (of equation 9) is not $\ll 1$ in most cases and can vary by orders of magnitude. This confirms the need for the empirical correction introduced in equation 9. Indeed, using the uncorrected formula 6 resulted in some cases in large deviations from the in-situ measurements (not shown). Therefore, we henceforth use for the spectrum inversion exclusively formula (10), which includes the non-linear reference brightness distribution correction. This formula also includes a regularization switch as described in section, although with the $R_2$ values found in the sea trials (figure 4), the switch plays a minor role in one case and none in the others.
Figure 5: Offshore sea trial (08-Feb-2022) comparison of bulk wave parameters with reanalysis data (hatched gray bars) and with a buoy which was located 15 km to the southwest (solid blue bars). Percentage differences are given in each bar for significant wave height (SWH), wave mean period ($T_{m2}$) and mean wave direction. The difference values in physical units between the UAV and buoy or CMEMS reanalysis values (whichever difference is greater in magnitude) are given in text next to each bar. Beneath them the absolute buoy parameter values are given as well. Reanalysis absolute parameter values are given in table 3.
Figure 6: First Tzuk beach sea trial (20-Feb-2022) UAV versus ADCP wave measurements. (a) UAV-derived sea surface height directional wavenumber spectrum in logarithmic scale, and in ‘from’ direction convention. A subset of the full measured wavenumber range is shown. (b) UAV-derived (in the black solid line) and ADCP-derived (in blue) frequency spectra. To demonstrate the effects of the spectrum processing steps defined in section , we also show the frequency spectrum of the raw UAV video graylevels (dashed and dotted lines, see further explanation in the main text). These raw UAV graylevel spectra are normalized for illustration purposes by a multiplicative constant such that at their lowest frequency they have the same value as the actual UAV-derived SSH frequency spectrum (in the solid black line). (c) Differences (in percents, shown as bars) between UAV and ADCP-derived bulk wave parameters: significant wave height (SWH), mean “from” direction (Θ), mean period (T02), and directional spread (σ, section ). The difference values in physical units (“d”) and the in-situ measured values (“v”) relative to which the percentages are defined, are given next to each bar in format “d rel. v”. All bulk-wave parameters and differences in panel c are computed over the ADCP-UAV overlap range of frequencies (between the black circles in panel b). In-situ-measured bulk wave parameters calculated over the entire in-situ spectral range are provided in table 1. Note that the relative directional difference is defined as the percent difference in (spectrally-weighted) mean wave directions relative to the worst case scenario, i.e. 180 degrees.

Figure 7: Second Tzuk beach sea trial (04-Mar-2022) results. The diagnostics in each panel are the same as in figure 6, except applied to the 04-Mar-2022 data of course.
Results: 08-Feb-2022 Research Cruise

In the 08-Feb-2022 offshore sea trial a co-located in-situ wave sensor was not available. Thereby we compare the 08-Feb-2022 UAV-derived wave bulk parameters against the CMEMS wave reanalysis data for the same date and hour (section ). The mean wave period \( (T_{m2}) \) according to the reanalysis was 3.4 s, corresponding to a wavelength around 20 m, which is resolved in the 80 m wide windows that we have used in the analysis. Therefore, calculation of the bulk wave parameters over the UAV frequency range is expected to produce similar results to their calculation over a frequency range extending into lower frequency values (as in CMEMS). The comparison shows that the UAV-derived bulk wave parameters are in good agreement with the wave reanalysis (figure 5, red bars). The differences in SWH, \( T_{m2} \), and \( \Theta \) are less than 10 cm, 0.2 s, and 30°, respectively. Note that this angular difference corresponds to just two angular bins of the reanalysis spectrum. We additionally compare the measurements against available data from a wave buoy positioned ≈15 km south-south-west of the UAV position in this sea trial. To compensate for the distance we use buoy data from two hours before the UAV measurements, which is approximately the time of travel from the buoy to the UAV based on the dominant wave speed and direction, keeping in mind that the results should be interpreted with caution (Soffer et al., 2020). The buoy-derived (figure 5, blue bars) SWH and \( \Theta \) are in almost perfect agreement with the UAV. The wave period is off by 0.7 s. We note that, based on a more detailed examination of the CMEMS reanalysis, two dominant swells were present, with periods near 3 seconds and 6 seconds, the latter with 50% smaller SWH signature, traveling in directions differing by 70 degrees. The comparison in this complicated two-swell state is quite satisfactory.

Results: Sea Trials with Co-Located In-Situ Sensors

In the remaining sea trials we had in-situ sensors co-located with the UAV observation area, which allowed comparison of frequency spectra as well as the bulk wave parameters (figures 6-9). In each figure we also present the UAV-derived vector wavenumber spectrum plot. While three-dimensional wavenumber-frequency visualization and analysis is possible as well (e.g. figure 3), we do not pursue it here.

In all cases, the UAV-derived frequency spectrum (black solid line in panel b of figures 6-9) agrees well in its overall shape and magnitude with the in-situ sensors (blue lines). Note that the spectra are in fair agreement (within their frequency overlap range) both in cases in which the wave spectral peak was within the UAV-measured range and in cases in which it was not (as in the Tzuk beach trials, in which the hover height was lower). The in-situ sensors reached lower frequencies than the UAV-derived spectra in all cases, since UAV flying altitude requirements limited the longest sampled wavelengths. The difference between the UAV-derived and the in-situ sensor frequency spectrum is smaller or similar in magnitude to the UAV spectral measurement uncertainty (red line in each figure) in all sea trials. The latter was calculated from spectral error theory (Thomson & Emery, 2014), with a \( p=0.05 \) significance level.

In contrast to the general agreement between in-situ frequency spectra and the processed UAV frequency spectra \( (S_{\zeta} \text{ in equation } 10) \), the “raw” graylevel spectrum \( (S_{I}) \) of the UAV-video has a completely different frequency distribution. That is so whether \( S_{I}(\omega) \) is derived by integrating \( S_{I}(k,\omega) \) over all wavenumbers (dotted lines in figures 6b-9b) or only over the wavenumber shell associated with linear waves (dashed lines) as done for \( S_{\zeta} \) (section ). Moreover, both the dotted and dashed lines were normalized to agree with the solid black line at one point, otherwise the formers’ (graylevel) units would not allow comparison with the (latter) SSH spectrum. Thus, the processing pipeline described in section is necessary to process the graylevel spectrum to SSH wave spectrum, and the processing is frequency and wavenumber dependent to a degree that it can differ by orders of magnitude from a conversion by a hypothetical multiplicative constant.

UAV-derived spectra reached higher frequencies than the ADCP and buoy spectra. The latter are more limited in resolution due to different factors, including footprint of ADCP acoustic beams, and of physical size of the wave buoy. In frequencies above 0.25 Hz (at the higher range of the in-situ sensors), the UAV spectral values are consistently lower than the in-situ sensors’. This is seen in the frequency spectra plots, and summarized succinctly in terms of the HFRatio values in table 3. The higher in-situ values is apparently...
accompanied by higher relative noise at these frequencies, as evidenced by their choppy spectral distribution. The higher apparent in-situ noise may be the cause of a high bias in the in-situ sensors in this frequency range, consistent with previous publications (Churchill et al., 2006; Work, 2008).

The bulk wave parameters (figures 6-9, panel c) are computed over the frequency range overlapping with the in-situ sensors. The UAV-derived bulk wave parameters (SWH, period, direction, and directional spread) compare relatively well with the validation in-situ sensors, i.e., within a few tens of percents. SWH deviation from in-situ measurement was smaller than 30% or 0.15 m in all cases, and less than 7% or 0.05 m in three of the four cases. Mean ($T_{m2}$) wave period agreed within 15% or 0.5 s. The mean wave direction ($\Theta$) was within 40° in all cases, and within 30° in three of the four cases. The mean direction differences are in general $\approx$50% or less of the in-situ-measured directional spread ($\sigma$) values, i.e., the mean direction differences may be partially due to estimation issues related to the directional spread (Herbers & Lentz, 2010). The differences in wave directional spread ($\sigma$) were within 25° in all cases, and within 10° in three of the four cases. These differences were 35% of the wave directional spread ($\sigma$) values themselves. Moreover, the absolute SWH, $T_{m2}$, $\Theta$, and $\sigma$ deviation values between the UAV and in-situ (ADCP or buoy) values are within the range of deviations between buoy- and ADCP- wave measurements in published reports (Work, 2008; Herbers & Lentz, 2010; Bouferrouk et al., 2016; Raghukumar et al., 2019; Lancaster et al., 2021).

In our sea trials we did not record video footage continuously over time intervals as long as were used in the in-situ sensors analysis (see section ). Due to these differences in time coverage, variability in the sea state during the in-situ sampling interval should result in differences in the in-situ and UAV measured spectra. The natural variability in wave SSH can be quantified by the Rayleigh distribution (Longuet-Higgins, 1953),

$$p(H) = \frac{1}{2H_{rms}^2} e^{-(H/H_{rms})^2},$$

(24)

where $p(H)$ is the probability of wave surface elevation value $H$, during a time frame with homogeneous statistics and wave surface variance $H_{rms}^2$. We have performed a Monte-Carlo simulation, drawing 100,000 batches of four samples of $H$ from a Rayleigh distribution. This corresponds to the four different UAV video time segments used in spectral calculation. The inter-batch standard deviation of intra-batch-mean $H$ is $\approx$25% of the distribution-mean of $H$. This limitation is indeed comparable to the deviations of UAV SWH measurements from the in-situ measurements, which was smaller 5% in three cases, and close to 25% in two more cases (figures 5-9).
Table 3: Sea trials results. The parameters $N_x$ and $N_t$ are defined in section . The following three columns provide minimal, mean, and maximal $R^2$ values (equation 15). Other columns summarize the deviation in bulk wave parameters relative to in-situ sensors, or (for the 08-Feb-2022 sea trial) the largest difference among the in-situ and reanalysis data. Validation metrics are defined in section .

<table>
<thead>
<tr>
<th>Date</th>
<th>Hour UTC</th>
<th>Location</th>
<th># Spatial Windows</th>
<th># Temporal Windows</th>
<th>$R^2$ Min</th>
<th>$R^2$ Mean</th>
<th>$R^2$ Max</th>
<th>Δ SWH</th>
<th>Δ $T_m$</th>
<th>ΔΘ</th>
<th>Δσ</th>
</tr>
</thead>
<tbody>
<tr>
<td>08-Feb-2022</td>
<td>10:45</td>
<td>Offshore</td>
<td>8</td>
<td>4</td>
<td>0.15</td>
<td>0.62</td>
<td>0.88</td>
<td>0.09 m</td>
<td>-0.7 s</td>
<td>-27°</td>
<td></td>
</tr>
<tr>
<td>20-Feb-2022</td>
<td>07:30</td>
<td>Tzuk Beach</td>
<td>3</td>
<td>3</td>
<td>0.17</td>
<td>0.68</td>
<td>0.93</td>
<td>0.15 m</td>
<td>0.5 s</td>
<td>19°</td>
<td>-25°</td>
</tr>
<tr>
<td>04-Mar-2022</td>
<td>10:15</td>
<td>Tzuk Beach</td>
<td>3</td>
<td>4</td>
<td>0.14</td>
<td>0.62</td>
<td>0.84</td>
<td>-0.01 m</td>
<td>0.2 s</td>
<td>39°</td>
<td>-10°</td>
</tr>
<tr>
<td>22-Jun-2023</td>
<td>05:55</td>
<td>Offshore</td>
<td>1</td>
<td>4</td>
<td>0.854</td>
<td>0.855</td>
<td>0.856</td>
<td>-0.02 m</td>
<td>0.5 s</td>
<td>-21°</td>
<td>3°</td>
</tr>
<tr>
<td>22-Jun-2023</td>
<td>06:35</td>
<td>Offshore</td>
<td>3</td>
<td>4</td>
<td>0.60</td>
<td>0.74</td>
<td>0.86</td>
<td>-0.04 m</td>
<td>0.1 s</td>
<td>-27°</td>
<td>9°</td>
</tr>
</tbody>
</table>

Figure 8: Offshore sea trial (22-June-2023) results for 05:55 UTC. The diagnostics in each panel are the same as in figures 6-7. Note that, due to a higher flight altitude, longer wave periods (or wavelengths) are covered by the UAV measurement here compared with validation figures 5-7.

Figure 9: Offshore sea trial (22-June-2023) results. Same as figure 8, but for 06:35 UTC.
Discussion

We have shown that the UAV-based estimation compares very favourably with in-situ observations in several test cases. A fuller characterization of the methodology by e.g. numerical simulation is postponed for future work. Here we qualitatively discuss several challenges, methodological weaknesses, and possible avenues for addressing them in future work.

Areal Coverage

To provide perspective on the wavelengths which can be resolved with our method, we present examples of ground coverage of UAV imagery in table TableTBD. The controlling parameters are the camera diagonal field of view (FOV), the UAV altitude $H$, and the image format. We choose a common image format for the examples in the table, 3840x2160. For simplicity, the number in the table were calculated assuming perfect camera optics in that the “instantaneous FOV” (angular aperture of each individual camera detector pixel) is uniform and isotropic. It follows from this assumption that

$$\text{FOV}_i \approx \frac{N_i}{\sqrt{N_x^2 + N_y^2}} \text{FOV},$$

(25)

where $N_i$ is the number of camera pixels along axis $i$ (camera $x$ or $y$ axis), and $\text{FOV}_i$ is the field of view along axis $i$. The $y$-axis length of the coverage area is

$$Y = 2H \tan(\text{FOV}_y/2),$$

(26)

and similarly for the $x$-axis. The smallest resolved wavelength ($\lambda_{\text{min}}$) is limited by the Nyquist frequency, i.e., a spatial period twice as large as the pixel length.

The longest wavelength which can be resolved in a single analyses sub-window (section ), hereafter $\lambda_{\text{max}}$, is the length of the largest square (i.e. analysis window) contained in the UAV imagery ground coverage region. We define $\lambda_{\text{max},3}$ similarly, as the largest value such that three squares of $\lambda_{\text{max},3}$ side length and 50% overlap (section ) along one axis are contained in the UAV imagery ground coverage region. The typical nearly 2x1 ratio of video format axes means that $\lambda_{\text{max},3}$ is just slightly shorter than $Y$ from equation 26 (denoting the short axis by $y$). Note that in the presented analyses we only analyzed and presented spectra up to a wavelength of $\lambda_{\text{max},3}/2$, since spectral resolution is lowest at the shortest wavenumbers, and since finite-window size and windowing effects might bias the estimated spectrum at wavelengths near the window length.

We summarize the $X$, $Y$, $\lambda_{\text{max},3}$, and $\lambda_{\text{min}}$ results for two representative camera altitudes and camera field of views based on the above equations in table TableTBD. Results for other altitudes can also be derived simply by linear scaling of the height. We also provide in the table the wave periods associated with each wavelength parameter, based on the Deep Water dispersion relation for frequency $\Omega(k)$ in the absence of a Doppler shift:

$$\Omega(k) = \sqrt{gk}.$$
Optical Paths and View Angles

Surface sea waves are optically observed by virtue of surface reflection of skylight. Other light paths serve effectively as noise in the estimation of the surface reflected light and the associated surface slope (i.e., wave state). Light scattered from the air directly to the camera is usually negligible in comparison with skylight reflection from the surface, except in low-visibility conditions such as haze and fog. However, the intensity variation due to light upwelling from beneath the surface can be higher than that of reflected skylight in some conditions, e.g., in very clear or shallow water or in fully clouded sky and near-uniform skylight intensity. That is so particularly when looking in nadir, in which the reflection coefficient magnitude is lower. Therefore, we intend to extend the present work to non nadir-camera orientations in future work. Slantwise camera orientation has the added advantage of covering a larger area. This can be important particularly where regulations prohibit flying high enough to cover the desired field of view in nadir. Properly oriented slantwise camera orientation can also reduce or remove sun glitter (Gray et al., 2022), which in some conditions may otherwise cause saturation and limit the obtainable wave signal.

Skylight Polarization

Since skylight polarization measurements were not taken in conjunction with our UAV videos, we treat here marine skylight as effectively unpolarized. In future work we will measure the degree of polarization of skylight and and account for it in the spectrum estimation, since each polarization component has a different reflection coefficient (per incidence angle). The zero polarization approximation is justified for incidence angles within $\approx 20^\circ$ from nadir, where the two reflection coefficients are almost identical; for reflection from sky portions within about $30^\circ$ of the solar position; in cloudy conditions or with high aerosol concentration (Sekera, 1957); Observations by (Guan et al., 2018) have also suggested that marine environments may have on average a degree of polarization around 10%. However measuring and taking account of skylight polarization would likely increase the accuracy of wave spectral power estimates, and allow a greater range of view angles.

In-Camera Processing

Standard digital cameras perform internally numerous processing operations of the raw digital images recorded. One of these operations is a non-linear transformation (sometimes called “gamma correction”) of pixel digital values. This is partially meant to imitate human vision processing of light conditions, and needs to be undone for applications which require that digital values be proportional to optical irradiance values. The nonlinear transformation is indeed included in the UAV cameras used here. A full inversion of this transformation can in principle be conducted (Kim et al., 2012), a step we will pursue in the future. However, we assume that this will result in many cases in only a modest correction to estimated spectra, since the nonlinearity correction appears in quantities raised to the same power (two) in the numerator and denominator our processing pipeline e.g. equation 10.

Another issue with contemporary camera standards is that the video is in most cases compressed before saving to file. While a large fraction of the standard MPEG4 compression (Marpe et al., 2006) is achieved via lossless algorithms, other algorithm parts might diminish the amplitude of higher frequencies and wavenumbers. The present methodology can be applied from higher cost UAVs equipped with “cinematic” cameras capable of recording uncompressed video. However, in keeping with the low-cost applicability purpose, we are in the process of investigating the frequency response of common video compression algorithms to synthetic surface
wave spectra, as we plan to report in the future. Such an analysis will define the surface wave frequency and wavenumber ranges which can be uncorrupted by compression.

**Summary and Conclusions**

We present and validate a new methodology for inference of surface wave spectra from low-cost UAVs, based on inverting the modulation by sea surface wave slope of skylight reflection intensity. Novel aspects of this work include the application of this concept to UAV imagery; the use of temporal (video) data for retrieval of full directional information, as well as for Doppler shift correction, and noise reduction; and a robust data-based methodology of regularized inversion of sea surface height wave spectra from optical imagery spectra.

We focus on nadir-imagery, which simplifies the observational marine operations as well as the analysis pipeline. No modification was conducted of the shelf-product UAVs. Thus the methodology opens a new avenue for wide scale deployment of surface wave measurements. Furthermore, UAVs bring many other advantages over classical platforms, such as mobility and ability to cover large areas in a short time span (Johnston, 2019; Gray et al., 2022).

We validate the methodology against observations in four UAV sea trials: observations 1 km offshore central Israel on two different dates, and two more dates of observations 20 and 30 km offshore. In all cases, the UAV-estimated bulk wave parameters including significant wave height, mean wave period, and mean wave direction were in good agreement with in-situ (ADCP or wave buoy) measurements (and with reanalysis where relevant). The frequency spectrum shape and magnitude were are also in fair agreement with in-situ measurements. Furthermore, the UAV provides high resolution surface elevation information in time and space which can be used to construct a full three-dimensional wavenumber-frequency spectrum. In contrast, common in-situ sensors measure little spatial information directly and derivation of 2D wave spectrum requires certain physical assumptions on the wave physics (e.g., see (Soffer et al., 2023) on the limitations of using potential wave theory). The in-situ directional data which is reconstructed can also be limited (commonly a two-component Fourier series in angle is derived from buoys). Thus, the presented method allows consumer-grade UAVs to perform, without modifications, as high-quality wave spectrum sensors. This can potentially open the road to a much higher volume of wave measurements globally, especially given the large number of hover-capable UAVs that are currently employed and being integrated in other research and technical activities (Streffer et al., 2017; Fiori et al., 2017; Johnston, 2019; Ridge & Johnston, 2020; Ubina & Cheng, 2022; Yang et al., 2022). A potential order of magnitude increase in wave data can be transformative scientifically as well as for society in general (e.g. for oil spill response, marine safety, search and rescue operations, etc).

Further development of the methodology is necessary in order to increase its accuracy and regime of applicability. One avenue would be by integrating concurrent measurements of skylight polarization, in order to take into account polarization-dependent sea-surface reflectivity. Although nadir imagery is particularly simple to obtain operationally, extending the present methodology to non-nadir imagery would increase operational flexibility as well as the signal to noise ratio of reflected skylight in many circumstances. Finally, it is likely that in high winds and high or breaking wave conditions the present methodology shall perform more poorly, partially since it relies on small wave approximations and partially since wave breaking produces foam which strongly modulates light reflection. Numerical simulation of system performance in different synthetic wave and sea conditions will be pursued in follow up work to delineate the accuracy and regime of applicability of the present methodology.
Acknowledgments

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The presented wave-estimation methodology is implemented as an expansion of the current-velocity estimation CopterCurrents open-source matlab package (Streßer et al., 2017), available from https://github.com/RubenCarrascoAlvarez/CopterCurrents. The new software can be received upon request.

This study has utilized data from a wind and wave buoy offshore of Israel, provided by the Israeli Oceanographic and Limnological Service (IOLR) data repository website ISRAMAR (https://isramar.ocean.org.il/isramar2009/).

This study has also utilized the Mediterranean Sea wave reanalysis product MEDSEA_MULTIYEAR_WAV_006_012 from the E.U. Copernicus Marine Service Information, doi https://doi.org/10.25423/cmcc/medsea_multiyear_wav_006_012.

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