Clouds in The Cloud:
Supplementary Material

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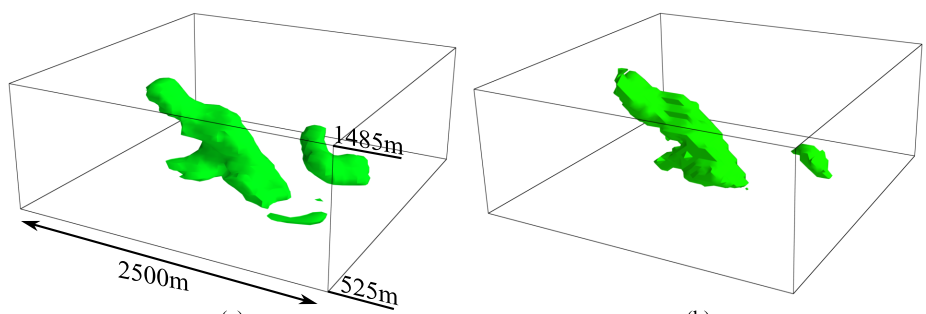
Abstract. In [1] we describe simulations and an appearance consistency measure that we used. The essence is in the paper, while in this supplemental document we give more details and results.

1 Simulations

In Sec. 8 of [1] we describe simulations, which enabled us to quantitatively assess performance of 3D cloud recovery. Here we give more details.

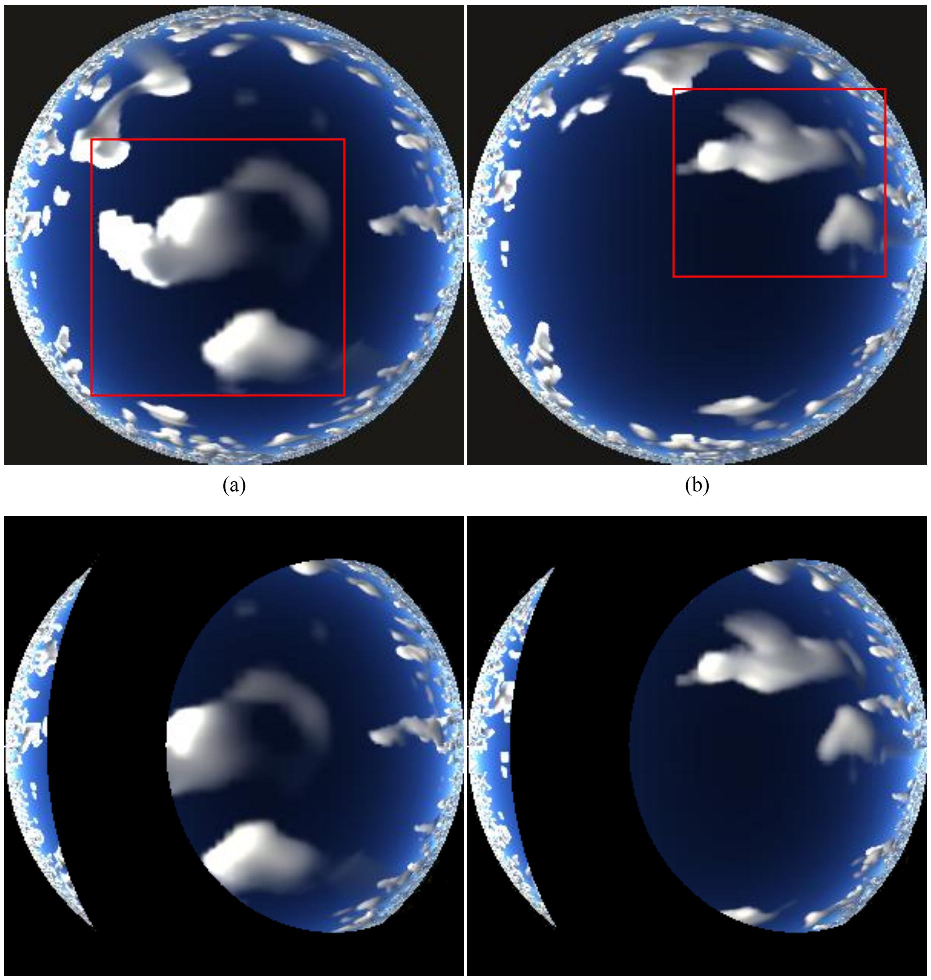
An atmosphere over $8\mathrm{km} \times 8\mathrm{km}$ was produced using off-the-shelf UCLA large eddy simulation (LES) [2]. It created a field of liquid water content (LWC) per voxel, which represented clouds between heights of $500\mathrm{m}$ to $1500\mathrm{m}$. Fig. 1(a) shows a $2.5 \times 2.5 \times 1.5\mathrm{km}^3$ subset of this atmosphere. The LWC field then affected radiative transfer, calculated using the discrete ordinate spherical-harmonic method (SHDOM) [3]. The solar zenith angle was set to $\frac{\pi}{4}$.



(a) (b)

Fig. 1. (a) The water liquid content distribution, showing clouds in the atmosphere. This is a major input to SHDOM calculations. (b) Reconstructed clouds.

Figs. 2(a,b) show images from two out of 100 synthesized cameras. The atmosphere above the cameras is marked by red rectangles in Figs. 2(a,b). The applied static Sun-blocker is tailored to solar trajectories in the latitude of Copenhagen. Figs. 2(c,d) show images using the simulated Sun-blocker. We reconstructed the cloud distribution in the atmosphere above the cameras. Fig. 1(b) shows one reconstruction result, as described in [1].



(a) (b)

(c) (d)

Fig. 2. Images synthesised using SHDOM and used in the reconstruction algorithm: (a,b) Two images (out of 100) of the same scene from different cameras. The red-marked rectangles define a region of interest, right above the network. (c,d) The same images, taken under a static sun-blocker.

2 Appearance Consistency Score

In Sec. 8 of [1], we describe a matching criterion we used to demonstrate space carving of clouds. Here we give more details about it, to ease reproducibility.

Basic space carving is usually based on pointwise photo-consistency. As we explain in Sec. 8 of [1], in clouds photo-consistency is sometimes not sufficiently discriminative. Dense SIFT [4] can be effective for non-rigid image matching. Similarly, dense SIFT can be incorporated into a space-carving scheme, to represent structural appearance of a projected voxel. Voxel k projects to a subset of the rays $\rho_k \subset \mathcal{R}$. For each ray $r \in \rho_k$, we measure the radiance $\hat{I}_t^{\chi}(r)$ (after correcting radiometric non-uniformities), where $\chi \in \{\mathrm{R},\mathrm{G},\mathrm{B}\}$ is the color-channel index. This forms a photometric vector $\mathbf{v}^{\mathrm{phot}}(r,t) = [\hat{I}_t^{\mathrm{R}}(r), \hat{I}_t^{\mathrm{G}}(r), \hat{I}_t^{\mathrm{B}}(r)]$, which is scaled globally to a unit bound.

In addition, each ray r corresponds to a pixel $\mathbf{x}$. From a patch around $\mathbf{x}$, a 128-bin SIFT descriptor is extracted [5], yielding a vector $\mathbf{v}^{\mathrm{SIFT}}(r,t)$. Each such vector is normalized such that $\|\mathbf{v}^{\mathrm{SIFT}}(r,t)\|_1 = 1$. Overall, the feature vector we use is $\mathbf{v}(r,t) = [\mathbf{v}^{\mathrm{phot}}(r,t),\ \mu\mathbf{v}^{\mathrm{SIFT}}(r,t)]$. Here μ determines the weight of SIFT vs. photometric descriptors. We used $\mu = 1/40$ throughout the experiment. Notice that the SIFT vector contains 40 times more values, so this choise of μ gives essentially equal power to the photometric and structural properties of the patch.

Element q of $\mathbf{v}(r,t)$ is $v_q(r,t)$. The values of this element, for all rays that intersect voxel k, form the set $\mathcal{V}_q(k,t) \equiv \{v_q(r,t)\}_{r\in\rho_k}$. Across viewpoints, the measured variance in this set is $\mathrm{VAR}[\mathcal{V}_q(k,t)]$. Appearance-consistency is based on summing the variances in the different components of the feature vectors:

$$P_k = \exp\left(-\sum_{q=1}^{131}\{\mathrm{VAR}[\mathcal{V}_q(k,t)]\}/\sigma^2\right) . \tag{1}$$

Here σ^2 is a global scale parameter which is set to $\sigma^2 = 0.1$ throughout our experiments.

References

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