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recovering a good image, which is defined here by the quality of its wavelet coefficients, will also result in an accurate phase map since phase information is largely contained within the wavelet coefficients. hence, our image recovery process is based on phase unwrapping using a phase-difference gradient method, which provides a good phase estimate. since the step size for phase unwrapping is the same as for the wavelet coefficients, we can initialize the algorithm without the risk of the unknown object becoming smaller than the initial reconstruction. we also noticed that, without the continuous optimization, the algorithm does not converge to the desired state if we are not using the phase information, since it contains primarily low frequency information. as a result, we show that the proposed algorithm converges regardless of the choice of the initial reconstruction when using both the phase-difference gradient optimization and the continuous optimization in the wavelet domain, although a longer optimization time is required. we also observe that the algorithm does not converge if the phase map is not used in the optimization. the fact that the algorithm provides a good fit for the reconstructed data confirms the accuracy of the reconstructed image, while a good fit for the phase map confirms that the algorithm provides an accurate phase unwrapping map, as expected. our algorithm also has an additional advantage: when used with real world measurements, the object position can be easily verified after the reconstruction, by comparing the reconstructed axial section with a corresponding section of the initial reconstruction. this comparison has been shown in fig. 2, where we compare a reconstructed axial section of a synthetic ground glass test object with a corresponding section of the initial reconstruction. we compare the two images by calculating the standard deviation of the intensity of the recovered object. even though we observe some noise in the reconstructed object, its intensity is close to the one of the initial reconstruction, revealing that the simulation contained the real axial position of the object.

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the sparsity constraint that we enforce in this approach is the same as the one used in the previously reported work on wavelet-domain compressive holography reconstructions 25 . the general principle is that the image and its wavelet coefficients are sparse over a dictionary of learned bases. the main difference in the implementation of this, compared to previously reported holographic work that has focused on imaging isolated objects 39, 40 , is that here our image sensor is configured to collect multiple holograms of the same scene at different sample-to-sensor distances. this arrangement allows us to disambiguate phase measurements from a given reference plane 9, 10, 41 , instead of relying only on those that belong to isolated blazed angles. at a given reference plane that corresponds to a given sample-to-sensor distance, we introduce a simple dictionary of learned bases, which consist of learned wavelets within a range of certain wavelet scales and orientations. in this work, we use the cdf 9/7 orthonormal wavelet family learned through the method of optimal basis generation 49 , which has been shown to perform well for digitally focused microscope imaging 48 . the wavelet coefficients at a given reference plane, which are used in the iterative reconstruction algorithm of section 2.2, are extracted from the full complex wavelet coefficients acquired at the closest plane, which are then further down-sampled by a factor of eight using 8th-order butterfly quantization50 . the scale of the dictionary bases are selected such that they represent different scales in terms of their distribution of energy on the local patches of the sample. the learned basis dictionary is constantly updated for each frame in each holographic acquisition process to account for the variation in the sample 9, 10, 41 . in addition, we enforce an overlap constraint on the dictionary bases that allows each frame to be reconstructed with a subset of the bases. this is due to the fact that in optical holography, each ray diffracted from a source region of the sample is typically not captured by a single hologram. as a result, the necessary basis dictionary is created from all the rays that are diffracted by the same diffraction region. this overlap constraint is enforced to make sure that similar images can be extracted from multiple distinct regions within the same hologram, which would significantly reduce the redundancy of the reconstruction, given the high degrees of measurement redundancy in our acquisition process. 5ec8ef588b