Bathymetric Retrieval From Hyperspectral Imagery Using Manifold Coordinate Representations

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Abstract—In this paper, we examine the accuracy of manifold coordinate representations as a reduced representation of a hyperspectral imagery (HSI) lookup table (LUT) for bathymetry retrieval. We also explore on a more limited basis the potential for using these coordinates for modeling other in water properties. Manifold coordinates are chosen because they are a data-driven intrinsic set of coordinates, which naturally parameterize nonlinearities that are present in HSI of water scenes. The approach is based on the extraction of a reduced dimensionality representation in manifold coordinates of a sufficiently large representative set of HSI. The manifold coordinates are derived from a scalable version of the isometric mapping algorithm. In the present and in our earlier works, these coordinates were used to establish an interpolating LUT for bathymetric retrieval by associating the representative data with ground truth data, in this case from a Light Detection and Ranging (LIDAR) estimate in the representative area. While not the focus of the present paper, the compression of LUTs could also be applied, in principle, to LUTs generated by forward radiative transfer models, and some preliminary work in this regard confirms the potential utility for this application. In this paper, we analyze the approach using data acquired by the Portable Hyperspectral Imager for Low-Light Spectroscopy (PHILLS) hyperspectral camera over the Indian River Lagoon, Florida, in 2004. Within a few months of the PHILLS overflights, Scanning Hydrographic Operational Airborne LIDAR Survey, LIDAR data were obtained for a portion of this study area, principally covering the beach zone and, in some instances, portions of contiguous river channels. Results demonstrate that significant compression of the LUTs is possible with little loss in retrieval accuracy.

Index Terms—Bathymetry, bottom type, hyperspectral imagery, isometric mapping, manifold coordinates, manifold learning, nonlinear estimation, optical data processing, optical image processing, remote sensing, spectral analysis, spectroscopy, water.

I. INTRODUCTION

The use of forward radiative transfer lookup tables (LUTs) has been suggested for retrievals from hyperspectral imagery (HSI) [32], [35]. To be comprehensive, tables must be large, and so, it is desirable to consider how one might best compress the spectra in these tables. We study a method of creating compact tables here that uses intrinsic manifold coordinate representations of the high-dimensional HSI samples. The approach is based on the extraction of a reduced dimensionality representation in manifold coordinates of a sufficiently large representative set of HSI [5]. The manifold coordinates for large hyperspectral scenes are derived from a scalable version [5] of the isometric mapping (ISOMAP) algorithm [17], [46]. In our scalable implementation, a solution for the manifold coordinates is obtained for a large representative “backbone” data set, and the manifold coordinates for large hyperspectral scenes are then solved by a reconstruction algorithm, which inserts all scene spectra into the coordinates defined for the representative backbone. The use of intrinsic coordinates for water applications is a natural choice because of the presence of nonlinearities in the data, resulting, for example, from the inherent attenuating nature of water and the complex scattering mechanisms present [34]. Building on our previous efforts for in water applications [3], [6], we focus on one approach to obtaining compact tables and limit our discussion primarily to just one retrieved quantity, namely, bathymetry. In this paper, we substitute ground truth obtained from the Scanning Hydrographic Operational Airborne LIDAR Survey (SHOALS) Light Detection and Ranging (LIDAR) as a surrogate for the ultimate goal of using a forward model, although we have already made some effort to apply manifold coordinates to model data obtained from a forward model via repeated execution of a radiative transfer model [24].

For aquatic applications, forward modeling has been one of several standard approaches to interpreting hyperspectral reflectance of water scenes, and commercial software packages such as Hydrolight [36] provide a ready-made implementation of the radiative transfer equations, allowing practitioners to input various water-quality parameters or bottom reflectances to assess the impact on the reflectance above the water surface. Tools such as these form the basis of the radiative transfer LUTs described in [35]. In [24], a number of the authors of the present work described the utility of manifold coordinates to model water hyperspectral data from the standpoint of radiative transfer theory. Several of the theoretical results of this study provide motivation for the investigation of manifold
coordinates for modeling in water data; a similar theme based on simple physical arguments also appears in [3] and [4]. In [24], we described several idealized cases to indicate the expected spectral response (reflectance), such as image subsets with fixed bottom but a varying depth. For this idealized case, the reflectance spectral data should display an exponentially decaying curve, really a high-dimensional decaying curve in spectral space. In the case of varying depths and more than one bottom type present, we showed that one expects to observe a set of decaying curves, one for each bottom type, that approach one another in spectral space as the depth approaches the optically deep case. Likewise, we pointed out that, for the case of a single bottom type, but variable water types present, we should also expect a set of decaying curves, one for each water type, which should meet near-zero depth. In the general case, we pointed out that we should expect multiple interconnected decaying curves when multiple bottom types and water types are present in a scene where variation in depth also occurs. These curves meet at various points, depending on local boundary conditions. Moving away from the idealized case, this earlier work also points out that when a sensor’s spatial resolution encompasses more than one bottom type within a single pixel, we can expect mixing between these exponentially decaying curves, which should lead to broadening of these curves or even hypersheets in spectral space.

Because the essence of manifold coordinate representations is the parameterization of high-dimensional data sets, we should expect to be able to identify and parameterize these threads and sheets in spectral space. In [3], we provided a concrete illustration of how depth can be parameterized in the dominant coordinates of a manifold coordinate representation, where a constant bottom type was inferred. Note that this does not assume in any way that we can identify a single 1-D parameterization of the data because influences in the water column and various bottom types will always play a role as just described. Indeed, this earlier example showed that the manifold coordinate representation was a curved tendril in a 3-D space. To fully characterize bathymetry, bottom type, and in water properties, we can only hope to identify a lower dimensional representation rather than a simple 1-D parameterization. We will return to this point later in Section II.

Before proceeding, we note that there have been a number of other approaches to modeling bathymetry from HSI as well as other remote sensing data types, such as SAR, multispectral, and INSAR [1], [15], [21], [26], [28]–[30], [33]. There are various tradeoffs to consider when choosing a sensor. Factors to consider include local oceanographic environment, data collection considerations such as coverage/swath, or temporal limitations (time of day) that affect some sensor choices. A comparison of some of these tradeoffs appears in, for example, the introduction of [33].

The remainder of this paper is organized as follows. Section II provides background on manifold coordinate representations, how they are calculated, and how they compare with other representations such as the minimum noise fraction (MNF) [22]. In Section III, we describe the study area and the HSI and ground truth data available for this study. Section IV describes the bathymetry experiments for the study area. In

Fig. 1. (Top) Manifold coordinates are in a linear space with orthonormal axes; these coordinates parameterize the original full \(N\)-dimensional spectral space. Linear distance in manifold coordinates corresponds to nonlinear (geodesic) distance in the full spectral space. (Middle) Manifold coordinates can be thought of as a local coordinate system throughout the original full spectral space. (Bottom) Nonlinear distances over the hyperspectral data samples are computed via a shortest path algorithm.

Section V, we present the results of our study, and in Section VI, we draw our final conclusions.

II. METHODOLOGY

A. Calculation of Manifold Coordinates

While we will not repeat all of the mathematical details of our scalable algorithm for deriving manifold coordinates in large-scale HSI [5], it is worth describing a few of the important features of manifold coordinate representations to set the stage for the rest of our discussion. The interested reader can consult [5] for further mathematical details.

Within the HSI community, linear algorithms such as the MNF [22] and linear mixing [9]–[14], [25], [41], [47], [49] are among the most widely used ones. Among linear algorithms, MNF, which is a noise-whitened principle component analysis, is the most closely related to manifold representations, in that manifold coordinates can be thought of as a nonlinear
Fig. 2. Comparison of linear MNF and nonlinear manifold coordinate representations of a PHILLS image subset derived from line 5. Note that the linear representation reaches a noise floor, while greater detail is revealed by the manifold coordinate representation in deeper areas. Numbers “1–2–3” and “4–5–6” indicate the corresponding order of the components used in each RGB combination; coordinates are ordered from most significant to least significant.

The methods used to calculate manifold coordinates reveal yet another aspect of the manifold coordinate representation, i.e., it preserves the nonlinear (geodesic) distance between the original data samples. That is, the linear distance in the manifold coordinates of a pair of spectral samples corresponds to the original nonlinear distance between the samples in the original spectral space (Fig. 1). Calculating nonlinear distances between samples is the cornerstone of the manifold coordinate calculation because the second-order variation (covariance) in these nonlinear distances is used to calculate the coordinate system using an eigenvector/eigenvalue decomposition. Assuming that a distance metric has been defined, such as Euclidean distance or spectral angle, the distance between any two samples is determined in the following manner. When samples are within the same locally linear neighborhood, the distance metric is used alone, but when samples are outside the neighborhood, the nonlinear distance is calculated as the shortest path distance over the surface of the data between the samples. This shortest path distance is computed using graph-theoretic methods such as Dijkstra’s algorithm [18], [43], which finds the shortest path via a relaxation algorithm and minimum priority queue, and links neighborhoods together through the shortest path in the overlap region between neighborhoods (Fig. 1). While the original ISOMAP [46] algorithm was based on an exhaustive pairwise calculation of these distances, more contemporary methods [17] have used the notion of identifying key landmark samples from which all nonlinear distances are calculated (a Nystrom approximation), and then projecting the remaining samples into an orthonormal basis derived from an eigenvector decomposition of the covariance of nonlinear distances between these landmarks. Our scalable approach [5] takes advantage of landmark processing, but it also incorporates several other important features such as the use of a fast-search technique to construct the neighborhoods; our method also recognizes that we cannot solve the entire problem of the coordinate optimization in memory when the size of the data set reaches remote sensing scale \((O(10^6)-O(10^7))\) pixels or greater, and
therefore relies on the idea of solving it for a “backbone” data set of representative samples drawn from throughout an image or image set, and then uses a reconstruction algorithm to insert the remaining samples (again using a fast-search technique). Challenges for manifold algorithms are related to defining the best way to determine the size of the locally linear neighborhoods and to determining the best method for selecting landmarks. In [5], we advocated the use of a “skeletonization” technique for choosing landmarks, while in [2], we advocated the use of information-theoretic methods to determine local intrinsic dimensionality and the best local neighborhood size. The results in this paper computationally follow the approach described in [5], while a future presentation will examine the utility of local intrinsic dimensionality [8].

B. Manifold Coordinate Representation of HSI Data

In a number of our previous publications, we have pointed out the potential for compression of HSI data using manifold coordinate representations [3]–[5]. Because the manifold coordinate representation provides an intrinsic coordinate system for the data, the representation provides a compact data-driven parameterization of the data. For water applications, this is an advantage because nonlinearity will be present due to the attenuating nature of the medium [34], and as pointed out in Section I, physical models suggest that a data-driven approach that parameterizes the local structure should be a useful representation of HSI water reflectance data [3], [4], [24]. In Fig. 2, we show this using a subset of flight line 5 from Fig. 3. In Fig. 2, we compare a linear MNF [22] representation of the data with that obtained by a manifold coordinate representation. Components are organized in descending order of significance in groups of three, represented as a red–green–blue (RGB) graphic, with one component assigned to each color axis. Note that the linear case quickly reaches a noise floor (see the eigen-spectral plot in the figure), which corresponds to a loss in detail in areas where the water column is deeper. In the nonlinear model, using manifold coordinates, details of these deeper areas are revealed in the lower order components. Note that, in the linear case, the eigenvalue/eigenvector decomposition is with respect to the covariance of linear distances between spectral samples, while in the case of manifold coordinates, the decomposition is with respect to nonlinear distances between spectral samples, i.e., geodesic distances along the surface of the high-dimensional data [4] [5]. Because the manifold coordinates can “follow” (parameterize) the nonlinear structure of the data, these coordinates elucidate structure in the deeper regions of the water column.

A second illustration is shown in Fig. 4. In this figure, we compare results for a subset of the data in one of the Portable Hyperspectral Imager for Low-Light Spectroscopy (PHILLS) scenes described in further detail in Section III. The particular
Fig. 4. (Top) MNF coordinates versus manifold coordinates for the PHILLS line 21 subset. (Left column) MNF and (right column) manifold coordinates. The RGB combinations shown are coordinates 1–2–3, 4–5–6, 7–8–9, 13–14–15, and 19–20–21. Note the greater detail provided by manifold coordinates in the lower order coordinates.

region shown is a subset of the PHILLS data showing only the water pixels overlapped by bottom-type reference data, based on aerial photointerpretation and ground survey [39]. These reference data were derived from the temporally closest available version of the associated vector data from 2003, the year before the PHILLS overflights. These data are described further in Section III. The PHILLS image subset in Fig. 4 was also at least partially overlapped by the SHOALS LIDAR of the Indian River shore and inlets mentioned earlier. Fig. 4 shows the progression in coordinate combinations again from largest to smallest for manifold coordinates and MNF coordinates. Note that by the time we have reached approximately component number 15, we are beginning to reach the noise floor in the MNF representation. In contrast, the manifold coordinate representation appears to be providing additional details about the water data.

For the generic bottom-type data overlapping this region, designated “unvegetated bottom,” “dense seagrass,” and “patchy seagrass,” we can consider the impact on their relative separability, as the number of components retained in each representation is varied. Note that the visual appearance of the manifold coordinates suggests that the lower order components may be giving us additional detail not available in the MNF coordinates. Fig. 5, which shows the Jeffries–Matsushita distance [5], [38], [45], a general measure of separability, shows that these generic bottom types are better separated by the manifold coordinate representation as we retain some of these lower order components. In particular, for the pair representing the most pure classes, unvegetated bottom and dense seagrass, after roughly four components are retained, the manifold coordinates always obtain the best separability. Note that similar crossover points are obtained for the comparison between unvegetated bottom and patchy seagrass as well as patchy versus dense
seagrass. This is consistent with what we have observed in Figs. 2 and 4, i.e., greater detail is offered in some of the lower components of the representation. In Fig. 5, we also show the average Jeffries–Matsushita distance over all category pairs for MNF, for the manifold coordinate representation, and for the manifold coordinate representation of data preprocessed by MNF. After ten components, the average separability of the manifold coordinate representation exceeds that of MNF. When the manifold coordinate representation is applied to data preprocessed by MNF, the crossover point, where manifold coordinate performance exceeds that of MNF alone, shifts to only seven components. On average, this suggests that some of the noise reduction capability of MNF is benefitting the manifold representation, while in all cases, the use of manifolds ultimately yields a better solution because it follows the data.

Returning to our earlier discussion about the expectation of tendril and sheet structures in water data motivated from physical theory in [24], we note that the scatterplots of components obtained using MNF versus those from manifold coordinates are entirely different (Fig. 6). In particular, in the examples shown, clear structures such as these are visible in 2-D projections of 3-D scatterplots and suggest that additional structure in the data is being found that may not be fully appreciated from only considering very broad generic categories such as the bottom types considered here. These structures may be related to detailed differences in bottom type (sand, silt, mud, and varieties of seagrass) and variations in aquatic constituents due to the presence of colored dissolved organic matter, suspended sediments, and the like.

C. Processing Chain

Our approach is based on the extraction of a reduced dimensionality representation in manifold coordinates of a sufficiently large representative set of HSI [5]. The manifold coordinates are derived from a scalable version [5] of the ISOMAP algorithm [17], [46]. In this paper and in [6], these coordinates were used to establish an interpolating LUT for bathymetric retrieval by associating the representative data with ground truth data, in this case from a LIDAR estimate in the representative area. In each experiment, a large representative set of spectral samples was derived at random from a subset of the available scenes shown in Fig. 3. A set of manifold coordinates for this representative “backbone” spectral set was derived using an enhanced ISOMAP algorithm described in [5]. A LUT was formed from this backbone set, with each entry in the table consisting of a manifold coordinate for the sample and its corresponding depth from the SHOALS LIDAR. Each scene in the 21 flight
Fig. 6. Two-dimensional projections of 3-D scatterplots of MNF and manifold coordinate representations for the line 21 subset. (Left column) MNF and (right column) manifold coordinates. (First row) Coordinates 1–2–3. (Bottom row) Coordinates 4–5–6. Note the presence of sheets and tendrils. Generally speaking, the MNF coordinates tend to be more diffuse.

lines shown in Fig. 3 was then reconstructed in the manifold coordinates of the backbone spectral data set, again using the reconstruction algorithm described in [5]. Fig. 7 shows example flight lines (lines 3 and 21) and various subsets of the corresponding manifold coordinates reconstructed in the manifold coordinate system of the backbone data set. In the example, only water pixels are shown in the area where subsequent flights by SHOALS overlapped the PHILLS flights. In these examples, overlap occurred in the vicinity of two inlets at either end of our study area. In the figure, the line 3 example is a scene from which samples were extracted during the backbone set formation in each of the three experiments to be described later in this paper, while line 21 represents a test area about 36 km to the south. Note that the dominant manifold coordinates (1–2–3) tend to highlight distinctions between the channel water (quite deep in line 3), the lagoon regions, the ocean water, as well as boats near the mouth of the inlet, while lower order components reveal further details, probably related to local variations in water constituents, bottom type, or, in some cases, possibly the presence of sensor artifacts that could be corrected with further processing. For each scene, every pixel (represented in manifold coordinates) in the scene was used as a query to the LUT. The closest element or elements in the table were identified, and the corresponding depth in the table was returned. When a single neighbor was used (this paper), the assigned depth was that of the closest member in the table; in other versions of this approach [6], we have obtained a closest set of neighbors and then interpolated by weighting the neighbors based on their relative weights in reconstruction. In some instances, using a nearest neighbor approach produces better results than an interpolated average of several near neighbors. This may depend on how comprehensive the LUT is. A schematic diagram of our overall approach is shown in Fig. 8.

III. DATA AND STUDY AREA

A. IRL, Florida

The Indian River Lagoon (IRL) is a 156-mile estuary located on Florida’s eastern seaboard [27]. The IRL is among the most biologically diverse estuaries in North America, containing habitats for over 4000 species of plants and animals in mangrove forests, salt marshes, and seagrass meadows. The ecological diversity is attributable to the fact that the IRL borders both temperate and subtropical climates located approximately between 27° and 29° N latitude [32]. It is well known that ecological diversity is common on the edges of habitats, as well as along ecotones, or ecological gradients (see, for example, [19]). Water circulation patterns within the estuary are wind driven rather than influenced by gravity or tide as compared to rivers or coastal ocean areas, respectively. Five inlets connect the IRL to the Atlantic Ocean, but this paper focuses only on the area between the Fort Pierce and St. Lucie inlets.

B. PHILLS Airborne Hyperspectral Data Collections

The airborne HSI of the IRL was collected by the Naval Research Laboratory’s PHILLS [16] sensor on July 14–15, 2004. The PHILLS collected HSI data in 128 spectral channels
Fig. 8. Processing flow. (Top) Construction of a LUT from samples derived from one or more images in the data set, with the table entries consisting of manifold coordinates and associated ground truth (in this paper, known depth from the overlapping SHOALS LIDAR data). (Bottom) Test scenes are reconstructed in the manifold coordinate representation, and then, each pixel in this representation becomes a query to the table, which returns the closest associated depth in the table or a weighted depth when more than one neighbor is requested.

### TABLE I

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Source Flight-lines</th>
<th>Table Size (No. Spectral Samples Extracted for LUT)</th>
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<td>379999</td>
</tr>
<tr>
<td>2</td>
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<tr>
<td>3</td>
<td>1-4, 9, 10, 12, 17</td>
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</tr>
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</table>

between 0.39 and 1.0 μm at 2-m ground sample distance (GSD). The data were later resampled to 64 spectral channels with 4-m GSD and 10-nm spectral resolution. Each scene had 500 pixels across track, and 25 hyperspectral flight lines of variable lengths were obtained across the two days of the exercise. Typical scenes contained from one to two million pixels. This study focuses on the first 21 lines shown in Fig. 3. Because of cloud cover on July 14 in the southern half of the study area (lines 11–21), the data used in this study were lines 1–10 from the July 14 flight, while lines 11–21 were derived from the July 15 flight. The data were atmospherically corrected using an in-house package known as Tafkaa [37]. The location of the flights is shown in Fig. 3, along with a mosaic of the imagery used in this study. SHOALS LIDAR data [20], [23], [44] were acquired within a few months of the PHILLS data collection campaign. In order to ensure consistency in coregistration, ground control points were identified in the SHOALS LIDAR images and the PHILLS data, and the PHILLS imagery was reregistered to the SHOALS data.

In addition to the LIDAR data, we have also used the bottom-type data mentioned earlier in Section II, which was the result of extensive photointerpretation from aerial photography coupled with field efforts to corroborate findings [39]. Although the ecological diversity is obviously far greater than the generic categories described in [39], it is still a useful reference. The main limitation is that the majority of this bottom-type data focused mostly on the interior lagoon of the Indian River region, while the SHOALS LIDAR data concentrated on the shoreline along the ocean. However, in a few areas, notably the inlets mentioned earlier, there are small areas of overlap between these two ancillary data sources.

The bottom-type data set consists of the following three quite broad and generic categories: unvegetated, dense seagrass, and patchy seagrass. There is also an algae class, but this did not overlap any of the areas where LIDAR data were obtained. The distinction of dense seagrass versus patchy seagrass is one of density, with the threshold occurring at the 50% cover level. The associated vector shapefiles used for delineation in Section II were based on the survey data from 2003.
IV. EXPERIMENTS

A series of experiments was conducted using different-size spectral LUTs derived from a subset of the PHILLS HSI scenes. Initial experiments focused on constructing LUTs from samples derived from the first four flight lines, which included data from one of two relatively deep inlet channels. These experiments confirmed that additional data were needed to represent the deeper ocean water in some of the scenes acquired later in the campaign. In subsequent experiments, we included samples from other scenes in the study region where this condition was represented.

In Experiment 1, samples were derived from each of the first four PHILLS HSI flight lines (lines 1–4 of Fig. 3 to form a spectral LUT). Because the PHILLS and SHOALS data sets had been coregistered, each entry in the table was associated with a depth derived from the corresponding SHOALS LIDAR data at the sampled pixel location. In Experiment 1, the table size was 379,999 pixels (Table I), proportionately sampled by the area covered, from each of the first four PHILLS flight lines. The resampled PHILLS imagery for the Indian River campaign, consisting of 64 spectral channels, were later reduced to 52 bands based on noise level. Manifold coordinates for this LUT were also derived using the enhanced ISOMAP algorithm that we previously described in [5]. The manifold coordinates of the LUT served as a manifold coordinate backbone for subsequent reconstruction of the entire PHILLS HSI scenes in manifold coordinates using the reconstruction technique that we also described in [5].

For subsequent manifold coordinate experiments, tests were conducted on the remaining samples not in the LUT from line 3 to assess within scene accuracy. Additional tests were also conducted on line 21 from the second day of the PHILLS HSI campaign in order to assess accuracy outside the region of model development (in Experiment 1, lines 1–4 from the first day of the campaign). These initial tests revealed that, while the deeper channel waters were modeled relatively well within the model (line 3) and outside (line 21), deeper ocean waters were not as well represented in the table. The subsequent experiments (Experiments 2 and 3) were designed to add progressively more examples from these deeper ocean water cases.

In all tests, for each test sample, the closest spectrum matched in the LUT returned the associate depth for the test
spectrum. Note that we have also used interpolating LUTs (via a reconstruction mapping) in the past [6]; however, in these experiments, which frequently used very small neighborhood sizes in the construction of the manifold, the nearest neighbor was the most robust, particularly as the number of manifold coordinates retained was decreased. Although other weighting schemes could be applied, involving the neighborhood, the experiments that we have done suggest that estimating the local intrinsic dimensionality of the manifold [2] may be necessary to obtain the best results. For simplicity, we consider only the simpler noninterpolating LUT result in this paper.

V. RESULTS

A. Table Size and Bathymetric Retrieval Accuracy

The three experiments examined progressively larger table sizes and were designed to demonstrate the importance of a comprehensive table that incorporates different water types, bottom types, and accompanying variations in depth. More important than the actual table size is the diversity of the LUT. This is particularly true for manifold coordinate representations because of the need to connect nonlinear shortest paths to develop the representation and, related to this, the practical necessity of developing a suitable backbone manifold coordinate representation into which the other samples may be inserted. Given this, it is not surprising that experience has demonstrated that a random sampling of representative data is generally a better choice for developing the backbone than having an image interpreter define suitable regions of interest that are representative through an interface. This is true for the present Indian River PHILLS data set and the LUTs described in this paper. We progressively built larger tables to develop a better representation of the variability in bottom types, water types, and depth seen across the study region. The typical root-mean-square (rms) error declined as the table size increased and became steadily more diverse because of the random sampling.

The issue of sampling is another way in which manifold coordinate representations can be distinguished from MNF. In order to achieve the MNF representation, noise statistics must be estimated from the data, and the usual implementation, as found for example in ENVI/IDL [42], involves the calculation of a shift difference between adjacent pixels in a spatially contiguous image, subset, or region of interest. This requirement of spatial continuity found in MNF for the input data is not a requirement for manifold coordinates which are only concerned with the local neighborhoods in spectral space. This difference in optimal sampling strategy between MNF and manifold coordinates meant that a strict comparison using exactly the same inputs was not possible. Nevertheless, we did construct an MNF solution for a sample set derived from a set of regions of interest derived by a human interpreter from the same set of lines used in the third manifold coordinate experiment listed in Table I. The table size of the MNF-based LUT was 702,008 pixels, about a 4% difference in size compared with that used for the manifold. The rms error over all depths for line 21 for the MNF case was 1.54 m, while for manifold coordinates, the result was 1.44 m, a 7% better result compared with that for MNF; in both cases, 30 coordinates were used for this comparison. We should not be too surprised by this result since the manifold coordinates should be able to model the known nonlinearity in water data by parameterizing this structure.

Initially, we also compared results for the two inlet regions in lines 3 and 21 partly because these lines contained both channel, lagoon, and ocean data, and also since these were, respectively, within the set of flight lines sampled to create the LUT (line 3) and outside this set (line 21). This allowed us to test the validity of the model for the test pixels not in the LUT but within the scene and compare the results against test pixels derived from the imagery not sampled in the LUT. Fig. 9 shows the bathymetry retrieved from the PHILLS HSI scene for both lines 3 and 21 in the subset regions overlapped by the SHOALS LIDAR survey using the manifold-based LUT from Experiment 3. Fig. 10 shows the corresponding accuracy of the manifold-based retrievals compared to the measurement by the SHOALS LIDAR at each pixel location. For reference, the statistical results in Fig. 10 also compare the manifold coordinate representation against using a LUT comprised of the full spectral data. Note that, for line 21, the spatially disjoint test case, using the full spectral data in the LUT, the rms error over all depths was 1.38 m, while for the manifold representation, it was 1.44 m, roughly a 4% difference in the overall rms error.

After comparing the inlet retrievals, the manifold-coordinate-based LUT bathymetry retrieval was completed for the entire study area using the Experiment 3 LUT. The results are compared against the SHOALS LIDAR in Fig. 11, showing the areas of common data between the PHILLS and the SHOALS. A composite error assessment versus depth for the entire study
Fig. 12. Mean and standard deviation of manifold coordinate LUT retrieved bathymetry versus SHOALS LIDAR estimated depth for all the test pixels not in the LUT (left) in the scenes sampled to create the LUT and (right) the scenes not sampled in LUT construction (spatially disjoint case). The red line indicates the graph of an ideal case.

TABLE II
AVERAGE DEVIATION IN DEPTH (IN METERS) RETRIEVED HSI BATHYMETRY VERSUS SHOALS LIDAR. EXPERIMENT 3 MANIFOLD COORDINATE LUT (731 035 SPECTRAL SAMPLES) VERSUS FULL SPECTRUM LUT

<table>
<thead>
<tr>
<th>Experiment 3, Manifold Coordinate LUT (Table Size 731035 Spectral Samples) vs Full Spectrum LUT</th>
<th>Results for Line 3, July 14, 2004 (within scene)</th>
<th>Results for Line 21, July 15, 2004 (spatially disjoint)</th>
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<td></td>
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area was compiled and appears in Fig. 12. The composite rms error for the test pixels not in the LUT but drawn from the same scenes where samples were collected for the LUT was 0.30 m over all depths. For test pixels in spatially disjoint flight lines, the composite rms error was 1.96 m over all depths; restricting the depth range successively to 10, 8, 6, and 4 m, we found that the rms errors for the spatially disjoint case were 1.62, 1.38, 1.07, and 0.76 m, respectively. For the spatially disjoint case (line 21), the mean departs from the SHOALS LIDAR result by more than a full standard deviation at 12-m depth and deeper; for the test pixels within the scenes sampled to produce the LUT, this departure occurs around 17.6 m. The principal contributing factor in these results appears to be adequate representation (spectral diversity) within the LUT. It is likely that a larger more diverse LUT would be needed to further bring down the error rate.

B. Comparison of Manifold Coordinate LUTs and Full Spectral LUTs

In Table II, we compare the accuracy of the bathymetric retrieval of the original full spectral data with that obtained when manifold coordinates of varying dimension are used in the LUT. The spectral backbone set associated with the LUT in Experiment 3 of Table I is the basis for comparison. Two cases are shown, with one representing a within-scene test, i.e., using line 3 from which some of the LUT samples were derived; however, for line 3, only the pixels not in the LUT were used in testing accuracy. Results for line 21, a spatially (36 km south) and temporally (one day) disjoint (i.e., not used in constructing the LUT) flight line, make up the second half of the table. In both cases, the difference between using the full spectral data and using manifold coordinates in the LUT translates to very small absolute differences in the accuracy of the retrieval. For line 3, the difference between the rms error of the full spectrum LUT and that of the manifold coordinate representation ranges from 14 cm (30 coordinates) to 26 cm (5 coordinates), while for line 21, a similar trend is obtained, where the difference ranges from 6 cm (30 coordinates) to 19 cm (5 coordinates).

VI. CONCLUSION

For water applications such as the remote retrieval of bathymetry studied in this paper, the size of the spectral LUT must be quite large, as this paper suggests. In all likelihood, further increases in table size would lead to further improvements in bathymetric accuracy. For this reason, the use of a
forward model [32] and [35] may be quite attractive compared with the prospect of collecting very large ground truth data sets. Note that the same approach here to compressing the representation with manifold coordinates, in principle, could be applied to a spectral LUT generated by a forward model, and some initial effort toward this end has already been described by us [24]. Because LUTs may be large, the ability to compress the representation into just a few coordinates is a desirable goal. The results of Table II indicate that compression of the HSI LUTs is possible using the data-driven manifold coordinate representation; the spatially and temporally disjoint test set shows very little difference in absolute retrieval error in the range between 5 and 30 retained manifold coordinates. The corresponding plots of mean and standard deviation shown in Fig. 10 indicate that, in the scenes sampled to construct the LUT, it is possible to retrieve bathymetry out to nearly 18-m depth for the test pixels not in the LUT. In general, note that, for scenes used in constructing the LUTs, where local water conditions are well modeled, we obtain significantly better accuracies at all depths. For these scenes, the test pixels that did not appear in the LUT were tested, and out to maximum true depth, errors never exceeded 0.5 m, and at the 10-m curve, errors never exceeded 0.3 m. In the spatially and temporally disjoint test set of Fig. 10, the overall variance in the retrieval is higher, and the retrieval works only out to about 11-m depth. Looking through the results from individual flight lines, we found that, out to 10-m depth, the rms error in retrieval accuracy for disjoint test sets is in the range of 0.9–2.1 m. This is expected, given the limited range of data available in the LUT for matching and, also, the physical limits imposed by the use of passive remote sensing. An important result, however, even with the table sizes used in this paper is the fact that, for the scenes not sampled in constructing the LUT, we obtain rms errors in most instances significantly less than 1 m out to a true depth of 6 m. A more comprehensive model, for this coastal regime alone, would require significantly greater represented variability, and therefore conceivably much larger tables, where the importance of a compact representation, such as that obtained with manifold coordinates, becomes increasingly relevant. We also found that the manifold coordinates may be useful in the retrieval of other in water properties such as bottom type. A limited comparison of separability for generic bottom types found an overall advantage for the manifold coordinate representation, suggesting that lower order components in the manifold representation can capture greater detail than that observed in the linear MNF representation.

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REFERENCES

A. Plaza, P. Martinez, R. Perez, and J. Plaza, “A quantitative and com-

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