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Automated segmentation of seafloor bathymetry from multibeam echosounder data using local Fourier histogram texture features

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Abstract

Patterns of seafloor topography represent regions of geomorphological feature types and the physiography governing the spatial distributions of benthic habitats. Topographic variability can be considered seafloor texture and can be remotely sensed by acoustic and optical devices. Benthic habitat delineations often involve distinctions based upon seafloor morphology and composition based upon acoustic data maps that are ground-truthed by optical imaging tools. Habitat delineations can be done manually, however, automation of the procedure could provide more objectivity and reproducible map products. Recently a technique using Fourier transforms (FT) to produce texture features called local Fourier histograms (LFH) has been used successfully to classify standard textures in grayscale images and automatically retrieve digital images from archives according to texture content [Zhou, F., Feng, J., Shi, Q., 2001. Texture feature based on local Fourier transform, ICIP Conference Proceedings, IEEE 0-7803-6725-1/01.]. We implemented a modified form of that approach by varying the spatial scales at which local Fourier histograms were calculated. A modified LFH texture feature classification technique was applied to multibeam echosounder (MBES) data from Piscataqua River, New Hampshire, USA, for automatic delineation of a seafloor topographic map into regions of distinct geomorphology and apparent benthic habitats. Automated segmentations were done by the LFH method on 1-m gridded MBES data, applying the local Fourier transform, used to generate the LFH, at spatial scales from 1 to 5 m. Seven seafloor texture classes were identified, corresponding to the primary substrate types and configurations in the study area as well as some previously unidentified regions and transitional zones. The texture regions serve as a physical habitat model for the seafloor, a basis for predicting

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benthic faunal inhabitants, their areal distributions, and serving as sampling strata for ground-truthing efforts.

Keywords: Automated segmentation; Seafloor bathymetry; Local Fourier histogram

1. Introduction

Topographic variability of the seafloor influences benthic community structure and ecological processes at many spatial scales (Bourget et al., 1994; Cusson and Bourget, 1997; Guichard and Bourget, 1998; Menge and Olson, 1990; Zajac, 2001). Traditionally topographic variability has been described based upon maps constructed from acoustic device (echosounder or sidescan sonar) data while biogenic features have been described using optical data from still or motion imaging devices. The overriding result is a mismatch of spatial scales between data, measurements, and interpretation of seafloor properties. Recent developments in multibeam echosounding (MBES), however, have resulted in detailed acoustic surveys that provide an unprecedented view of the seafloor at a broad range of spatial scales. Using MBES data, digital elevation models (DEM) or digital terrain maps (DTM) (two-dimensional rasterized data representing elevation of the seafloor or depth) are produced that represent nearly continuous coverage depth measurements of the seafloor and reveal distinguishable texture patterns that represent topographic variation patterns, or geomorphological regions. In shallow water (tens of meters deep), features with vertical dimensions of centimeters and horizontal dimensions of decimeters to meters can generally be distinguished, such that habitat and microhabitat characteristics are easily discriminated.

Benthic habitat delineation has recently become a worldwide ocean science priority, and MBES data-based seafloor maps appear to provide the best basis for initial delineation of the seafloor into geological and geomorphological regions (Mayer et al., 1999; Todd et al., 1999; Kostylev et al., 2001). In turn, a physical habitat model developed by interpretation of those regions can be used to model distributions of benthic biology using any available biological or fisheries data, organism–substrate interaction models, or direct sampling. Recent studies have utilized MBES and acoustic backscatter data to provide geological (Todd et al., 1999) and biological habitat (Kostylev et al., 2001) maps, but their delineations were done manually. Manual segmentation (by visual appearance) and delineation are inherently subjective and therefore can be inaccurate. Simple approaches to the automated segmentation based on first order statistics of topographic data may be sufficient in some cases, but often fail to distinguish areas with different biogeological processes, morphology or composition. Thus, there exists a need for a robust, automated delineation approach that is accurate, unbiased, and fast, even for datasets that can contain billions of measurements.

One possible approach to automating the delineation of seafloor regions involves texture analysis of MBES-derived DTMs representing seafloor topography data. Some common texture analysis techniques include grayscale co-occurrence matrices and Gabor functions (Ware, 2000; Zhou et al., 2001). In particular, Gabor filters were based upon models of human vision perception of texture, thus Gabor functions can be used to detect and segment grayscale image textures in a manner similar to how the human visual system would (Ware, 2000). However, human perception is biased, and digital terrain models of the seafloor can incorporate differences due to data projections or nonstandard exaggerations incorporated for visual effect, thus reinforcing the need for a more objective methodology, less dependent on human perception.

One such approach that was recently developed for texture feature construction uses local Fourier transforms (FT) to accurately describe the local spatial distribution of values (Zhou et al., 2001). It has been shown that this technique provides a reliable means of classification of grayscale texture images (Brodatz textures) as well as automatic retrieval of images from digital archives according to texture content. The texture features produced by the local FT technique called local Fourier histograms (LFH), performed as well or better than grayscale co-occurrence matrix features for automatic classification of 13 Brodatz textures. In addition, Zhou et al. (2001) demonstrated that LFH texture features performed similarly to Gabor features for automated retrieval of Brodatz texture images, such that the average overall recognition ratio for 108 Brodatz textures was 70.56% for LFH and 69.63% for Gabor.

A technique incorporating texture features similar to LFH, but denoted local spectral histograms (LSH) was recently developed by Liu et al. (2001) that might be more flexible but also more subjective in that it involves user choice of a set of filtering operations prior to generating the texture features.

We have applied the LFH texture feature classification for automated classification and segmentation of the seafloor. A modified form of the LFH texture feature classification technique was implemented by varying the spatial scales from which data were used to calculate the local Fourier transforms. The technique was applied to multibeam echosounder (MBES) data for automatic segmentation of a seafloor elevation map into regions of distinct geomorphology and apparent benthic habitats. The accuracy of segmentation results was verified using historical sediment sample data and sediment maps (Ward, 1995), as well as underwater video imagery and diver observations.

2. Study area

The study area was located in the mouth of the Piscataqua River, a well-mixed estuary (Swift et al., 1996) flowing between New Hampshire and Maine, USA (Fig. 1) and exchanging water with the Gulf of Maine. The freshwater supply to the Piscataqua River originates in a watershed in southeast New Hampshire and Maine and includes six tributaries, three of which flow first into Great Bay, however, each of the tributaries is dammed at some point. The total watershed area is 2334 km^2. In the mouth, the channel is oriented north–south, then turns abruptly to near due west at Fort Point, NH. The Piscataqua is a tidally dominated system, with tidal amplitudes (half of the tidal range) of 1.3 m near the study area (Swift and Brown, 1983). Average total discharges for all the tributaries combined is about 32 $m^3\ s^{-1}$ (Short, 1992). Maximum average cross-section and time averaged current speeds near the study area are 0.5 ms^{-1}

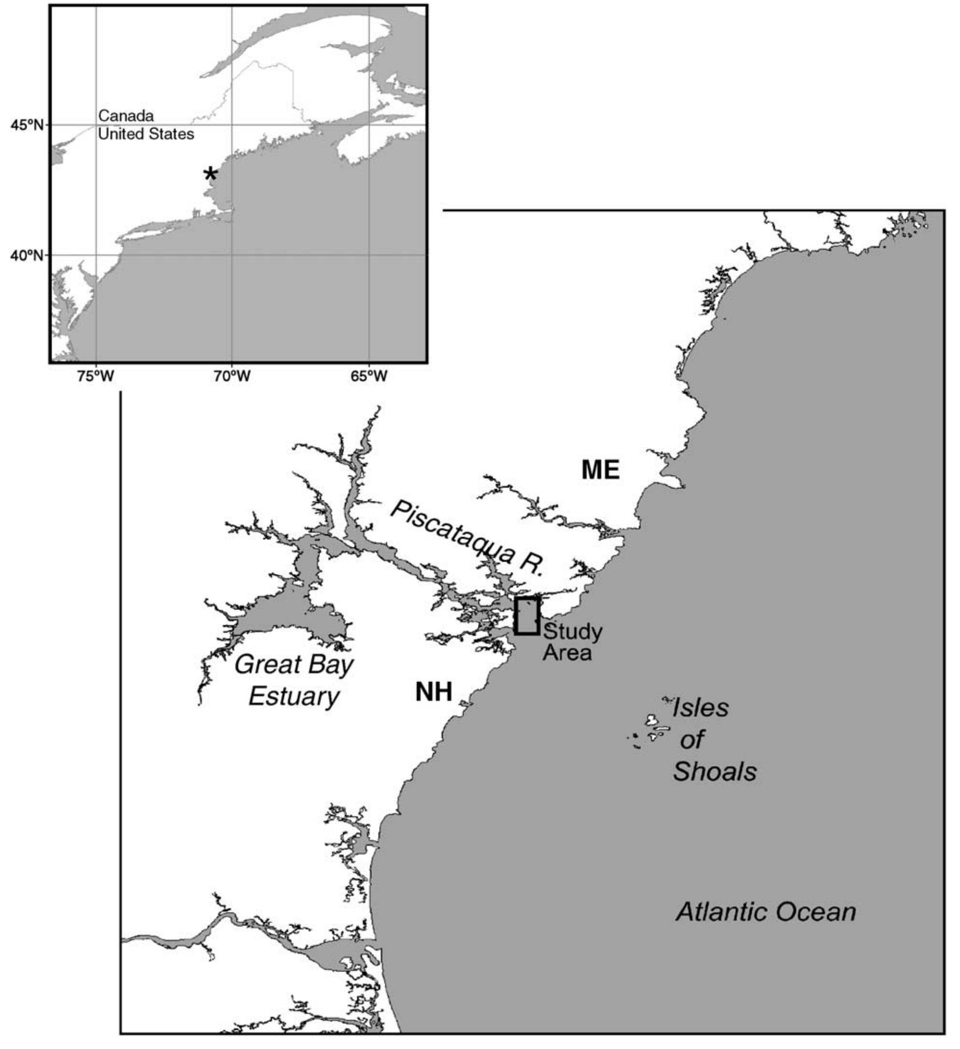


Fig. 1. Study area consisted of a section of subtidal waters in the Piscataqua River, between New Hampshire and Maine, USA. The asterisk in the small map marks the area enlarged.

(spring) and 0.4 ms^{-1} (neap) (Swift et al., 1996). However, in narrower parts of the river upstream, current speeds can reach 2.2 ms^{-1} (Swift and Brown, 1983) to 3.1 ms^{-1} (Short, 1992).

Primary substrates in the Piscataqua River mouth study area were previously mapped by sediment core sample data (Ward, 1995) and include intertidal and subtidal bedrock, gravelly channel sediments, and a central channel sand sediment region. The sandy central channel region was recently determined from the MBES data and by diver and video observations to be a rippled sand wave field, consisting of 5- to 10-m wavelength, 0.5- to 1-m height sand waves composed of fine to medium sand and fine shell hash.

3. Methods

3.1. Dataset

The dataset used for developing an automated segmentation procedure was a 1-m gridded surface representing the bathymetry in the mouth of the Piscataqua River, New Hampshire, USA (Fig. 2). The gridded bathymetry was constructed using data collected

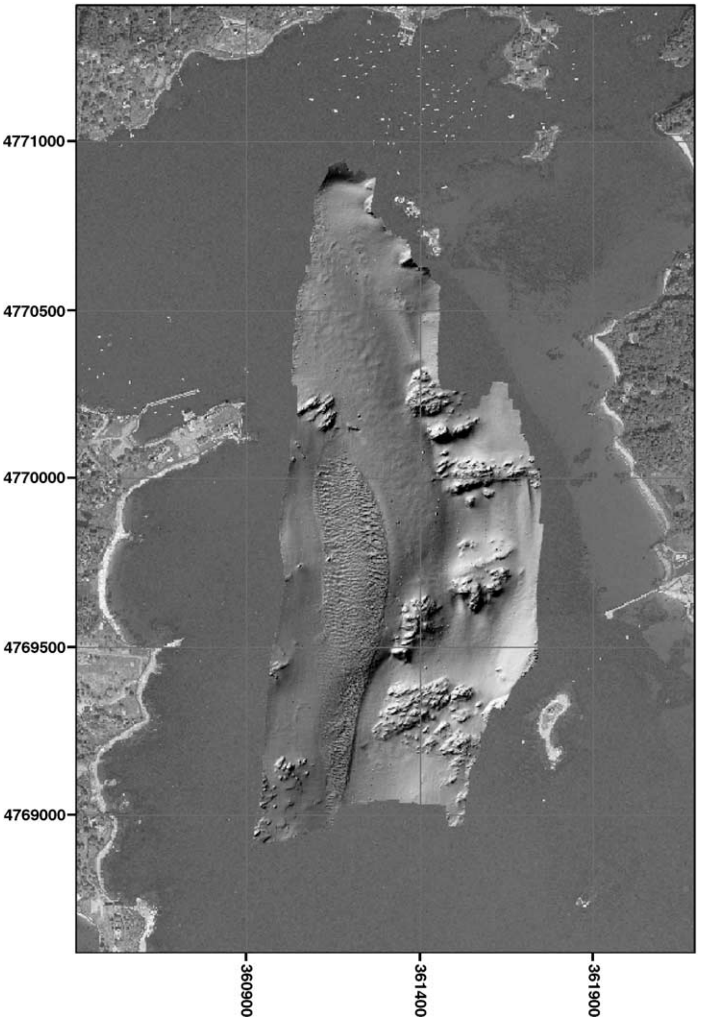


Fig. 2. Bathymetric digital terrain model (DTM) from the mouth of the Piscataqua River, NH, gridded to 1 m, UTM projection, zone 19N. Constructed from Reson 8125 multibeam echosounder data, collected by SAIC for NOAA and UNH JHC-CCOM, July 2000.

with a Reson 8125 multibeam echosounder, collected aboard the R/V Coastal Surveyor (UNH) by Science Applications International (SAIC) as part of the Shallow Water Survey 2001 Common Dataset (see Mayer and Baldwin, 2001). Positioning was accomplished using an Applanix POS MV 320 (Positioning and Orientation System for Marine Vessels). Data were cleaned and the grid was constructed using Hydrographic Information Processing System (HIPS, copyright CARIS, New Brunswick, Canada); data are presented on a Universal Transverse Mercator (UTM) projection, zone 19 north. The dataset covered 839 by 2034 m, where the center of the lower left corner grid cell originated at UTM Northing 4,768,915 m, Easting 360,918 m (latitude 43.0602 North, longitude 70.707 West).

3.2. LFH texture features

We use a modified implementation of the local Fourier histogram (LFH) texture analysis and discrimination technique described by Zhou et al. (2001). The processing procedure involved calculating a local FT for every data point (grid cell, pixel or node). The Fourier coefficients characterize the frequencies present in the signal, i.e. the signal's roughness. Zhou et al. (2001) described texture features by considering only the immediate vicinity of a node in two-dimensional rasterized data. On a square grid, such as in grayscale images and DTMs, that vicinity consists of eight nearest neighbors, enumerated consecutively to form a one-dimensional signal. Fourier coefficients of this signal reflect local isotropic roughness of the area around the node.

Eight Fourier coefficients from the eight element one-dimensional signal may be interpreted as four magnitude and four phase values. Only magnitudes are used for the LFH texture features. In addition, the average depth value from the block was removed from coefficient 0 value (also known as the direct current or DC value, and representing the mean value of the series) prior to constructing the histograms in order to eliminate artifacts related to mean depth effects. To characterize texture for using the LFH technique, it is required that a group of nodes be used. For all nodes in a square block 10 by 10 m (block sizes of 5 by 5 m and 20 by 20 m were also tested), the Fourier coefficients are calculated, then accumulated into histograms. One histogram, with eight bins each, is developed for each magnitude coefficient. Thus, the block of nodes is described by an LFH texture feature vector with 32 elements formed by concatenating the individual histograms (LFH feature vector elements 0, 1,...7 contain the histogram for the 0th magnitude coefficients, elements 8 through 15 contain the histogram for the 1st coefficient, etc.).

Our implementation allows for varying radii and block size at which the local FT was applied and LFHs were accumulated. Our modification to Zhou et al. (2001) was to calculate the Fourier coefficients at not only the nearest neighbor data, but also data from a larger neighborhood, combined in a manner (depth averaged for eight $\pi/4$ radian angular sectors within a specified radial distance about each node) that maintained the same format input signal to the FT (eight element, one-dimensional signal). LFH texture features from the expanded neighborhood describe texture at broader scales. An alternative method for examining multiple spatial scale texture using LFH would be to use only the eight nearest neighbor data, but to apply the LFH to data gridded at various scales.

3.3. Class grouping

Classes were constructed using fuzzy k-means cluster analysis (Minasny and McBratney, 2000). Seven cluster group classes (cluster groups) were chosen after examination of results from 4 to 10 classes and showed either lack of separation of primary sedimentary regions of Ward (1995) when too few classes were chosen, or excessive patchiness with too many classes. The number of classes chosen was meant to provide correspondence with substrate types for which prior knowledge existed (in the study area, there were four) and additional configurations and transitional zones evident from visual inspection of the DTM. Table 1 summarizes the classes, areal coverages and provides general descriptions of the type of bottom delineated. In order to provide some assessment of what the texture classes represented in terms of composition, beyond the geomorphological properties apparent from visual interpretation of the acoustic data (sand waves and rock), the LFH map was compared to an existing substrate map and substrate point data from Ward (1995).

3.4. Representative LFH texture features

After cluster analysis classification, representative LFH texture features were constructed using all LFHs from each class. Initial representative LFH texture features included data from all classes, even those determined to be misclassifications. Final LFH representative texture features were constructed using only data from classes determined to represent distinct regions accurately according to comparisons with Ward (1995) samples and visual interpretation of the terrain model, such that LFHs from apparent misclassifications were not used in construction of the representative LFHs. The representative LFH texture feature vector was meant to represent only the clear cases where textures clearly corresponded to particular substrate configurations.

Table 1
Substrate types found in each LFH class region, and total areal coverages of each LFH class

LFH class	General description	Sediment class of Ward (1995) samples located in each LFH class region	Raw LFH coverage (m^2)	Majority LFH coverage (m^2)
1	Smoother sedimented bottom texture 1	sG, sG, gS, gS	111,725	92,960
2	Rougher sedimented bottom texture 1	gS, sG, mS	187,060	182,589
3	Smoother sedimented bottom texture 2	gS, msG, sG, sG	172,785	199,122
4	Sand waves	S	221,360	219,995
5	Rock	NR, sG, mgS	111,017	126,986
6	Rougher sedimented bottom texture 2	gS, gS, sG	185,340	216,774
7	Steep, smooth marginal slopes	NA	61,819	67,438

Substrate classes were based upon sediment samples from Ward (1995), with type descriptions in terms of Folk's (1954) mud, sand, and gravel. Sediment classes include sandy gravel (sG), gravelly sand (gS), muddy sand (mS), sand (S), muddy gravelly sand (mgS); within class 5 (rocky), there was one station where no samples were recovered (NR); no samples were taken (NA) within LFH class 7. Areal coverage (rounded to nearest m^2) of each LFH texture feature class in the study area, for raw LFH results (5-m radius, 10- by 10-m block), and majority filtered results (majority value in 30- by 30-m block around each grid cell).

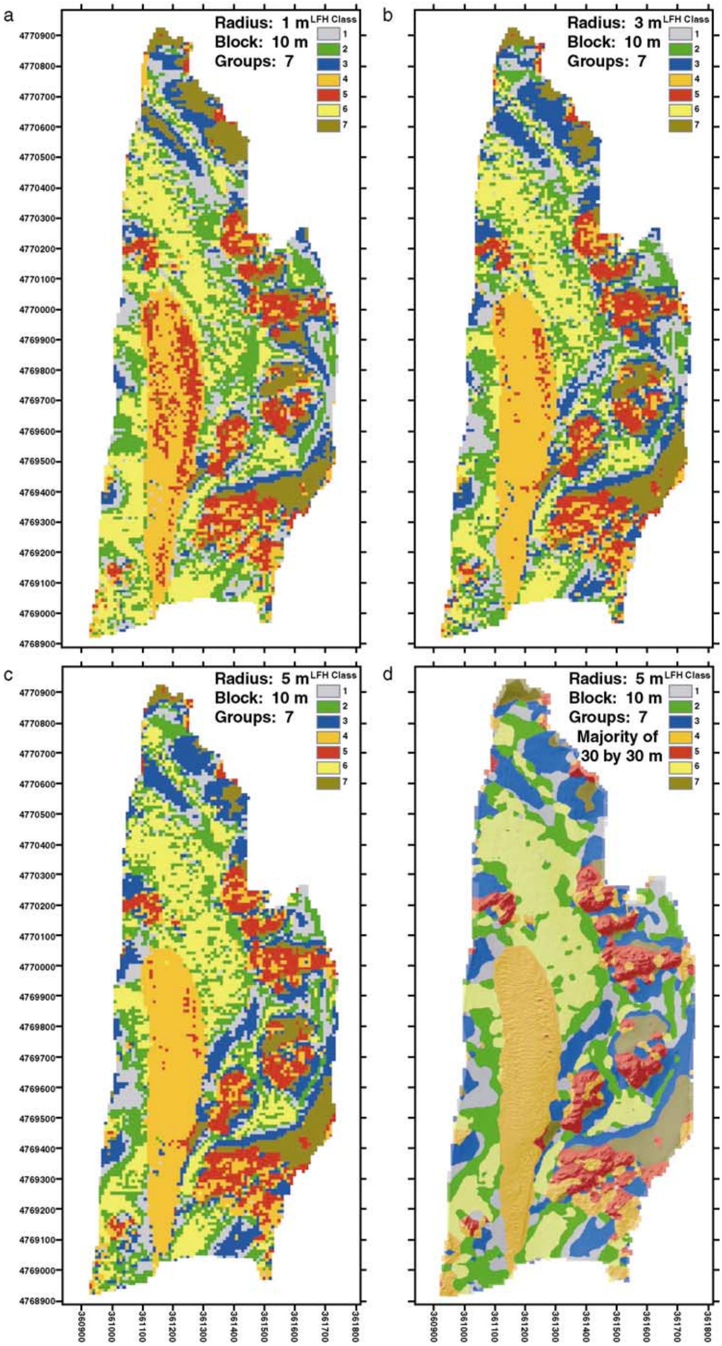
4. Results

The LFH texture feature classification segmentations of the seafloor corresponded well with the various geomorphological and sedimentary regions mapped by Ward (1995) in the study area. LFH classification results were robust, generating similar segmentations across several spatial scales of application (Fig. 3). Seven cluster classes were chosen as best representing the variety of apparent geomorphological features in the study area. Fewer classes led to clearly different morphologies being classified as the same, more led to subdivisions within groups (excessive patchiness).

Application of LFH to cell nearest neighbors (radius = 1 m) corresponded directly to the procedure described by Zhou et al. (2001). The resultant map showed several regions with mixed texture classes. Because more uniform regionalization was sought, the neighborhood scales were increased. Results for radii of 1, 3, and 5 m are shown in Fig. 3a–c. With increasing neighborhood scale (radius), more uniform regions were produced, at the expense of potentially missing small patches of unique texture class. Using a radius of 1 m, i.e. just the eight nearest neighbors, many texture feature blocks were considered to be misclassifications, and were particularly obvious in the sand wave field (Fig. 3a). Increase of the scale to a radius of 3 m resulted in more consistent regions. The best balance between regional consistency and oversimplification was produced using a radius of 5 m for these data at this grid size. The LFH map produced using a 5-m radius was filtered to generate more coherent regions by adopting the majority value from 30- by 30-m blocks as the new cell value (Fig. 3). These regions also suggest sampling strata for ancillary data collection, and produced a clean map for comparison with the DTM and analysis within geographic information systems.

Relating the LFH texture feature classes to sediments and substrates by comparison to point sediment sample data and sediment maps (Ward, 1995) showed that LFH class 4 corresponded to the large central channel bottom sand field. LFH class 5 corresponded to subtidal and intertidal bedrock. Ward samples in the LFH class 5 regions revealed only sandy gravel and muddy gravelly sand, however, other Ward samples in rocky regions (including one in LFH class 5 region) listed no data because no sample was retrieved when the grab sampler actually landed on rock (Table 1). Based upon the Ward (1995) map, all the other classes would be lumped into the gravel class, however, examination of the individual sediment samples in the LFH study area shows that the regions delineated according to LFH class 7 were not represented by any sediment samples, only interpolation. LFH classes 1, 2, 3 and 6 were represented by 11 sediment samples, primarily composed of sandy gravel and gravelly sand (Table 1).

Fig. 3. Segmentation of Piscataqua River mouth bathymetry by local Fourier Histogram (LFH) texture feature classification using coefficients 0 through 3 and varying spatial scales from which data were gathered (varying neighborhood radius) to generate texture features. LFH Texture feature classes from (a) neighborhood radius of 1 m, (b) neighborhood radius of 3 m, (c) neighborhood radius of 5 m, (d) neighborhood radius of 5 m where the original LFH class value for each cell was replaced by majority value from the surrounding 30- by 30-m block, and LFH map draped onto bathymetric terrain model surface. Coordinates are in UTM Eastings and Northings, zone 19 north.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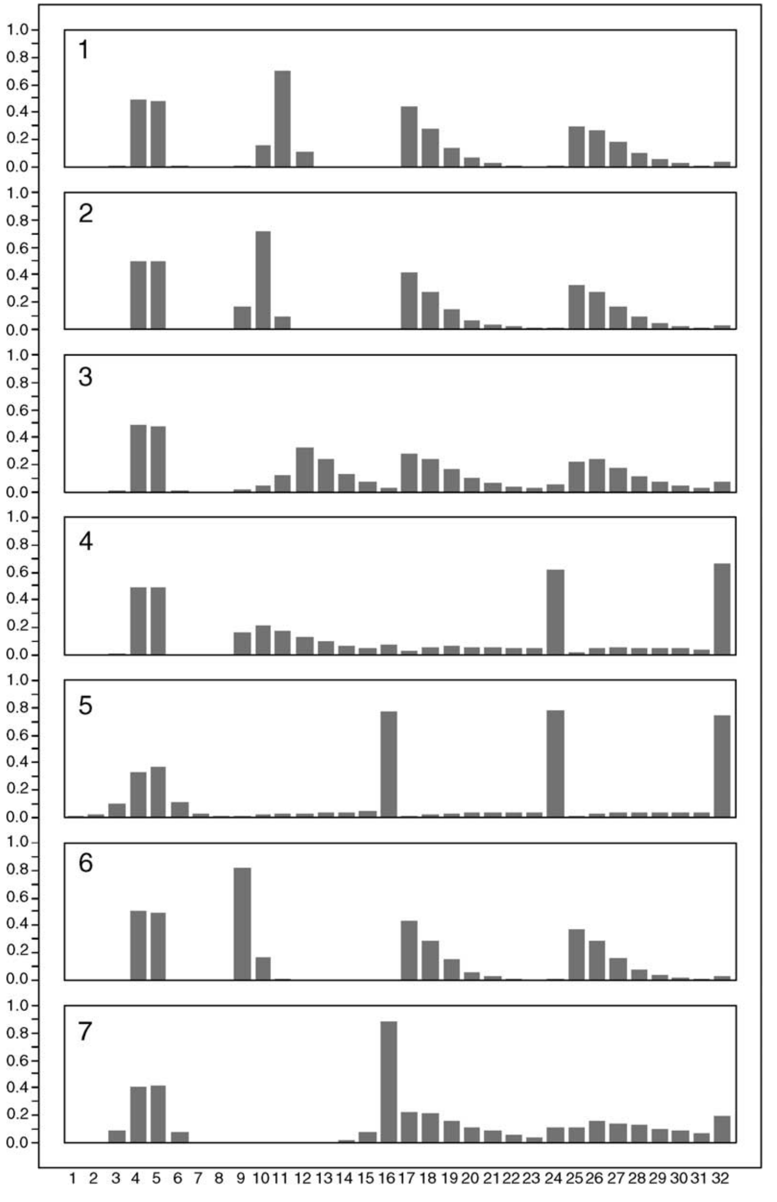
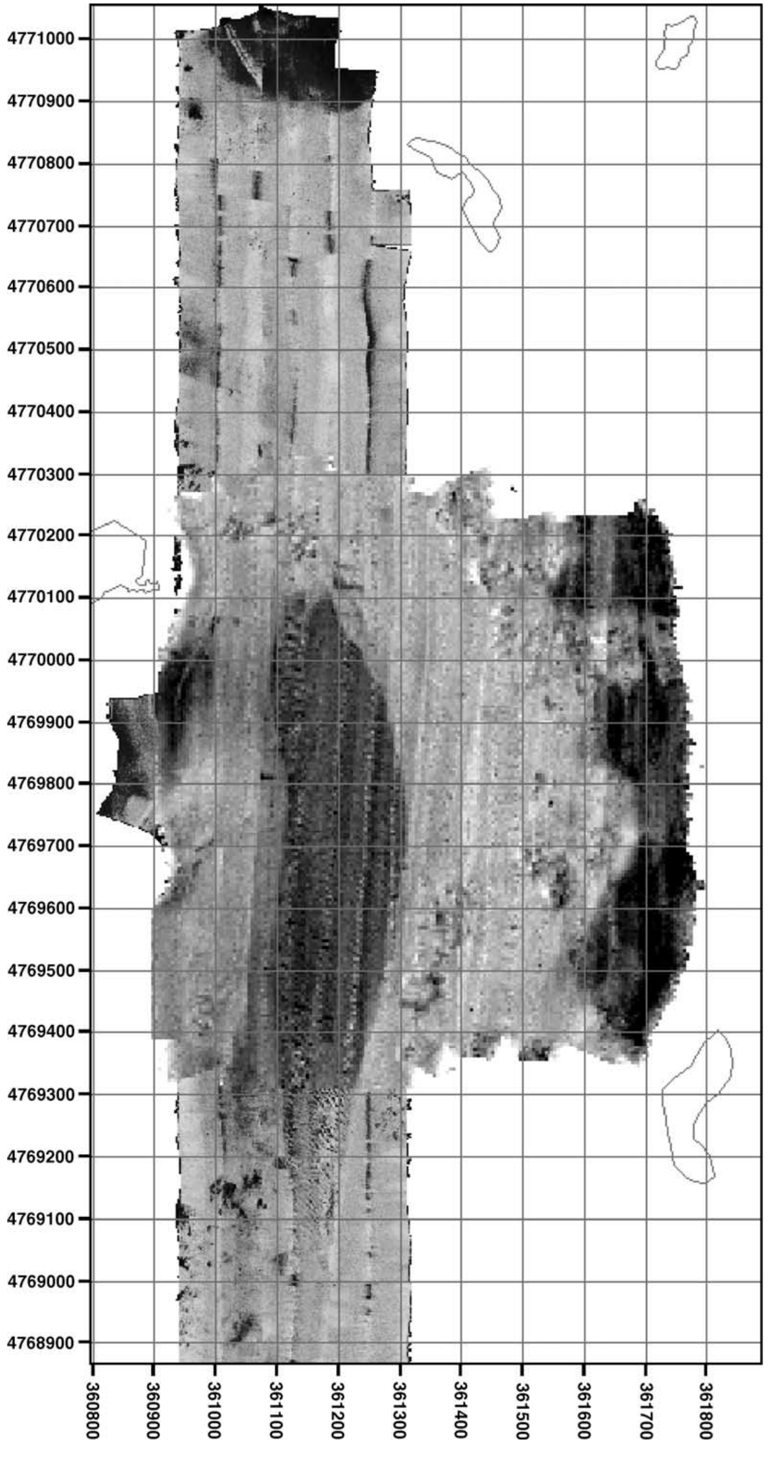


Fig. 4. Representative histograms for seven LFH texture feature (radius = 1 m, block = 10 by 10 m) classes from cluster groups. Each successive eight bins represent the distribution of an individual local FT magnitude coefficient. Thus, bins 1–8 represent local FT coefficient 0-mean, bins 9–16 represent coefficient 1 magnitude, bins 17–24 represent coefficient 2 magnitude, and bins 25–32 represent coefficient 3 magnitude. Clustering was done using fuzzy k-means method (Minasny and McBratney, 2000).

Total areal coverages of majority filtered LFH class ranged from 67,438 m^2 (class 7) to 219,995 m^2 (class 4) (Table 1). Classes 2, 3, 4, and 6 all had coverages on the order of 200,000 m^2. Classes 1, 5, and 7 had coverages on the order of 100,000 m^2. Representative LFHs, produced using the mean of all LFHs by class, showed distinct differences between classes according to distributions of the various FT coefficients used (Fig. 4). The distributions of the four Fourier coefficients used to construct the local FT maps and the LFHs were apparent in the LFHs. The seven different LFH classes varied most by distributions of coefficients 1, 2, and 3. Variation of the distributions of coefficient 0 was not as pronounced (Fig. 4) as the other coefficients' distributions, in general. LFH classes 5 and 7 had broad distributions of coefficient 0, the other classes all had narrow coefficient 0 distributions (Fig. 4, LFH bins 1 through 8). LFH classes 1 and 2 had representative LFHs similar enough to suggest consolidation of those classes, except that the distributions of coefficient 1 were slightly different (Fig. 4, LFH bins 9 through 17). Distinctions among the other representative LFHs reinforce that textural differences existed between seafloor regions segmented by LFH. No single coefficient distribution showed enough difference across classes that have been used for separation. Regardless, when the individual histograms were combined as the LFH feature vector, class differences were distinct. In other words, the texture LFH features represent complex spatial variation of seafloor topography.

5. Discussion

Geomorphological regions were discriminated with high efficiency using LFH texture feature classification. Regions distinguished by LFH analysis were suggestive of substrate type and sediment distributions. LFH maps showed patterns similar to the relative backscatter intensity map (Fig. 5) and the substrate map delineated by Ward (1995). The LFH texture feature classes from the Piscataqua River mouth were determined to represent most simply: rock outcrops, a sand wave and ripple field, and gravelly channel regions (Table 1). Those same regional types were delineated by Ward (1995) based upon core and grab samples and some sidescan sonar data. In addition, LFH texture classes existed for transitional regions and other bottom textures suggestive of slightly different geomorphologies that were either lumped into broad substrate classes by Ward (1995) or previously unsampled. Diver observations and underwater video showed these to include regions of sandy sediments with large (typically >0.5 cm) shell fragments (represented by classes 1 and 2, see Fig. 3). The apparent disparity between seafloor type regions corresponding to LFH textures and sample data for some LFH classes was indicative of two issues: (1) in rock outcrop regions, grab samples did not recover the rock itself, either recovering no sample or recovering sediment interspersed amidst the rocks, and (2) delineations and descriptions of bottom type have inherent scale-dependent generalization attached that can affect correspondences between maps from different sources and methodologies. In addition, substrate heterogeneity is likely to accompany any particular seafloor texture, therefore, concise generalization to seafloor composition is not recommended.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Some textural differences appear to represent similar substrates with different roughness configurations that are likely related to sediment transport, spatial and temporal variations in hydrodynamic effects. Those are important factors to benthic organisms, affecting benthic assemblage structure and function. A reassessment of organism–sediment interaction (OSI) studies by Snelgrove and Butman (1994) emphasized the need to consider hydrodynamics and material transport in order to strengthen OSI models. If seafloor texture patterns relate to material transport and hydrodynamic processes, as suggested, then regions delineated by seafloor texture represent spatial extents of the benthic physical environment within which a process occurs at particular frequency and with certain intensity. Therefore, texture maps of the seafloor can provide insight about the benthic biology by not only revealing physiographic constraints and regionalization of seafloor feature types, but also by delimiting areas within with particular hydrodynamic influences. Seafloor topographic maps analyzed for texture or roughness distributions are subtidal analogues to the synoptic maps generated by airborne spectrographic techniques for intertidal and shallow subtidal water. Although biological attributes of the system and organism–sediment interactions may make more difficult the interpretation of spectrographic data used to construct synoptic maps, those attributes may lead to insights about how to remotely sense related processes (Paterson and Black, 1999). Similarly, physical and biological factors influencing seafloor texture at various spatial scales must be studied in order to accurately assess how and why differences in texture in acoustic maps of subtidal waters indicate differences in substrate characteristics and benthic habitats. Those efforts will likely lead to refinement of the interpretation of acoustic-derived seafloor maps and better methods for seafloor exploration.

Because of the resolution of the Piscataqua River dataset, discrimination of region types by LFH was done to much finer scales than previous sediment type delineations based primarily upon interpolation of sparse point data; such is the strength of MBES-derived bathymetry data. Although the apparent associations exist between LFH classes and substrate types, LFH classes are not simply representative of substrate alone; they represent bottom texture which, in a dynamic estuarine environment such as the Piscataqua, is driven by interactions between existing substrate composition, newly delivered sediments, fluid dynamics, and biological modifications.

Representative LFHs from correctly classified data, determined by the investigators, provide feature vectors that can then be applied to other data. Thus, representative LFHs can serve as training features representative of particular geomorphologies, and can be used to directly determine the bottom texture and type for new data.

The spatial scales of feature variation were important and did cause some apparent misclassifications, the most apparent were the areas within the rock regions that were classified the same as the sand wave field. The geometry of the rocks and sand waves was

Fig. 5. Acoustic backscatter mosaic image covering part of the study area. The backscatter mosaic consists of data from a Klein 5000 and a Konsberg-Simrad EM3000 system, mosaiced separately, gridded to 1 m (Klein) and 5 m (K-S), then combined and gray levels adjusted.

similar enough in those cases to inhibit distinction by LFH analysis. The term apparent misclassifications was used because there may have been a physical or biological basis for the apparent misclassifications: sediments may have accumulated in the depressions among rocks, or soft-bodied animals and plants may have covered the rocks, thereby affecting the morphology.

6. Conclusions

We have developed an automated, objective method for delineating physical benthic habitats that can be used to model biological habitats, prior to sampling the biology, using historical biological data and assumptions about organism–substrate associations. LFH texture feature classification served that purpose, and was automated, except for the choices of number of classes and texture spatial scale. The appropriate scales of application of LFH should be determinable by optimization procedures, allowing more automation and generalization of the procedures. In addition, despite the good initial results of LFH texture feature segmentation of seafloor topography, alternative segmentation techniques and comparisons to quantitative measures of roughness should be implemented. Areas with apparent misclassifications should be examined directly to determine their character. When applying the segmentation procedure to new data, an "unknown" or "new" class should be introduced to allow for textures that do not correspond to the existing LFH texture features. That will allow exploration and classification of new areas without restricting descriptions to only known types.

The LFH segmentations serve to regionalize seafloor texture patterns and therefore geomorphological, sediment and hydrodynamic interaction regions. Therefore, LFH segmentations result in a predicted physical habitat model for the seafloor. That, in turn can be used to predict the initial benthic biological habitat model, particularly distributions of primary benthic community constituents or functional group types, dependent upon the detail of prior knowledge of the biological assemblages in the study area. One of the strengths of segmentations made using LFH on MBES-derived bathymetry lies in their ability to provide a context for detailed in situ seafloor investigation data. On the other hand, interpretations about the ecosystem made using MBES should incorporate such detailed data, otherwise the descriptions are still as coarse as the data resolution. Thus, there are limits to interpretations made using only the MBES seafloor topography data that should be addressed by rigorous, accurately georeferenced, and innovative ground truthing methods. In particular, we seek methods that can provide information about types and rates of changes occurring in the transitions between regions segmented using LFH, and determine the true local variability of seafloor textures that might represent habitat patchiness. The majority-filtered map provided a clean and easy to interpret regionalization of the seafloor in the study area, however, the apparently noisy representations might be valid for certain attributes. Determination of small spatial scale variability could not be done using the Ward (1995) sediment map or sparse samples, therefore, we suggested a simplified depiction of seafloor region types in order not to speculate without supportive data. For new seafloor explorations, it is likely that even less supportive or ground-truthing data will be available, therefore, we believe that maintaining a simple initial model is a practical approach.

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