Coastal water mapping using satellite hyperspectral data

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Conventional hyperspectral processing methods applied to current-generation satellite hyperspectral data improve results.

Mapping coastal water for the purposes of monitoring quality and identifying submarine fresh-water springs is especially important near urban centers and in gulfs, where pollution can be particularly problematic and the need for fresh water great. But these areas pose special mapping challenges. For example, in one such area in the Evvoikos Gulf in central Greece, sea water, urban waste, industrial waste, and chlorophyll from submarine vegetation are in continuous motion due to winds and currents, creating a mixture that is very difficult to map by traditional methods. In many cases, fresh water from surface or submarine springs further complicates conditions.

In recent decades, multispectral and thermal satellite data has become available for coastal water mapping. Thermal satellite data has yielded favorable results for detecting submarine springs¹ and pollution, based on the temperature differences between sea water and fresh water or pollutants. However, the low spectral resolution of available multispectral data and the similarity of spectral responses from mixed features have led to poor classification results. Current-generation satellite hyperspectral data, such as that gathered by Hyperion, a hyperspectral sensor aboard NASA's Earth Observing-1 satellite, presents an opportunity for new research and better results. Hyperion's pushbroom grating spectrometer collects 242 bands, each with a nominal bandwidth of 10nm and a pixel size of 29.88m. In this study, analysis of two Hyperion images acquired in summer 2004, in situ GPS data, and ground spectro-radiometer measurements were tested for coastal water mapping. The approach developed for analysis of the hyperspectral data can be summarized in the following steps (see Figure 1).

The first step aimed to reduce the complexity of the image by dimensionality reduction, which compresses the image data to a few meaningful bands. Initial visual inspection of the original 242 bands suggested that many were dominated by noise

Figure 1. Flowchart for hyperspectral data analysis and classification.

and others contained no useful information. Control of statistical histogram parameters confirmed this, and 138 bands were selected as a data set for further processing. Next, the minimum noise fraction transformation method (MNF)² was employed to remove noise and compress these into 118 images, from which 38 were selected according to minimum noise content criterion. Additionally, variance and the Schlapfer sensibility index³ were applied to in situ radiometer measurements of reflectance and radiance. This defined two additional data sets, one based on radiometer reflectance and one based on radiance measurements, each containing nine hyperspectral bands determined to be most sensitive to sea-water properties.

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Figure 2. Image classification using the spectral angle mapper (SAM) algorithm reveals chlorophyll (green) over an oblong zone along the east coast of the Gulf. Violet represents fresh-water currents.

The second step aimed to classify the images according to the number of targets—or spectra corresponding to specific materials—present in every pixel. The algorithms for this type of analysis can be divided in two major categories. The first assumes that every pixel contains information dominated by only one target. This category includes classifiers developed specifically for hyperspectral imagery, such as spectral feature fitting and the spectral angle mapper (SAM).⁴ However, natural surfaces are rarely composed of a single uniform material; more commonly, they are made up of mixtures of spectrally distinct materials, such as minerals, alteration products, vegetation, water, and shadows that cause spectral mixing when they are represented in a single image pixel. Thus a second category of algorithm includes classification methods such as complete linear spectral unmixing^{5,6} and mixture-tuned matched filtering⁷. These detect quantities of a target that are much smaller than the pixel size itself, using con-

vex geometry-based methods⁸ to isolate extreme pixels within an image and then represent these in a multi-dimensional display.⁹ According to these methods, the most extreme pixels are assumed to represent spectrally homogenous examples of the mixing targets and they are identified by repeatedly projecting n -dimensional scatter plots onto a random unit vector.

In this study, SAM, linear spectral unmixing, and mixture-tuned matched filtering algorithms were applied on the three data sets derived by the first step. As the exact number of the targets in the specific area was unknown, several tests were performed assuming numbers of targets varying between three and 17 for each data set.

In the last step, results were interpreted and evaluated. The classification of the 38 MNF bands yielded the worst results, failing to detect the underwater springs. However, the classification results of the nine bands selected based on radiometer measurements were better, successfully detecting underwater springs. Since the same bands were included in the first data set, it seems clear that the high number of bands prevented detection of the springs when evaluated by the same classification techniques. The Hyperion data yielded quite satisfactory results, detecting and classifying chlorophyll and freshwater currents (see Figure 2). Classification was successful independent of the data set and algorithm used, and is presented with different colors depending on the data set and classification method. In the middle of the Gulf there is an in-water stream with a west-east direction that was also detected and classified in all the data sets. In general, it seems that as the number of targets decreased, the classification result improved when the linear spectral unmixing and mixture-tuned matched filtering methods were applied. However, when using the SAM algorithm, increasing the number of targets seemed to result in improved classification results. Further, prior knowledge of the number of targets in a scene would be essential for successful classification.

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