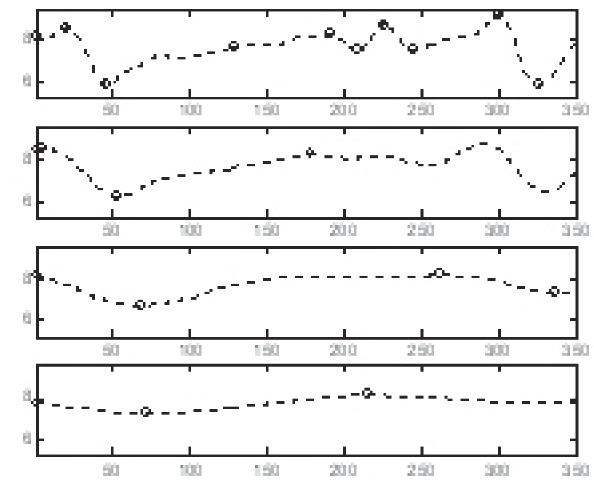

Figure 1. Unidimensional multiresolution sparse dataset, from level -1 to 6.

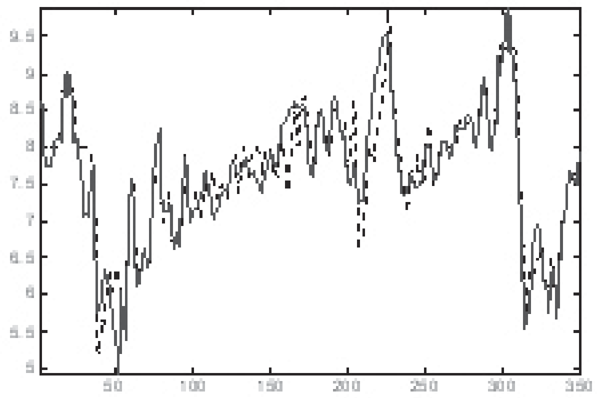

Figure 2. Reconstruction using CLEAN interpolation and 15 iterations on our method (continuous line) and original vector v (dotted line).

In Fig.2 we have the reconstruction using a CLEAN interpolation as a first guess, and with 15 iterations on our iterative model-based multiresolution approach. We measured a Normalized Absolute Error,

$$NAE = \frac{\sum_{n=1}^{N} \left| \{v\}_n - \{\hat{v}\}_n \right|}{N}, \quad (1)$$

In Fig.2 we obtained a NAE ≤ 3•10-2, It must be pointed out that this quantitative result remains similar with other kinds of initial interpolation, linear, cubic o splines, but qualitative results are better with an initial CLEAN interpolation, due to the long gap on the values from sample n. 95 to sample n. 180.

3. Conclusions

We have presented an extension of any interpolation method with a dyadic and sparse multiresolution dataset, with heterogeneous distribution of sparse data at different resolutions. We made a recent extension to a sparse multiresolution image dataset and a vector-field dataset for their reconstruction, and preliminary results are very interesting. Further research should be the tuning of this methodology to sensed data from applications, especially on the design of the model for the analysis and synthesis schema for the multiresolution decomposition given a sparse multiresolution dataset.

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SATELLITE IMAGE GEOREGISTRATION FROM COAST-LINE CODIFICATION

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Abstract

This paper presents a contour-based approach for automatic image registration in satellite oceanography. Accurate image georegistration is an essential step to increase the effectiveness of all the image processing methods that aggregate information from different sources, i.e. applying data fusion techniques. In our approach the images description is based on main contours extracted from coast-line. Each contour is codified by a modified chain-code, and the result is a discrete value sequence. The classical registration techniques were area-based, and the registration was done in a 2D domain (spatial and/or transformed); this approach is feature-based, and the registration is done in a 1D domain (discrete sequences). This new technique improves the registration results. It allows the registration of multimodal images, and the registration when there are occlusions and gaps in the images (i.e. due to clouds), or the registration on images with moderate perspective changes. Finally, it has to be pointed out that the proposed contour-matching technique assumes that a reference image, containing the coastlines of the input image geographical area, is available.

1. Introduction

In many image processing applications using satellite images and specifically in those related to oceanographic studies, it is necessary to compare multiple images of the same scene acquired by different sensors or images taken by the same sensor but at different time instants. Typical applications include multitemporal classification, recognition, and tracking of specific patterns, multisensor data fusion, and environment monitoring [1]. Such a comparison of multiple images requires either their spatial registration or their georeferencing. Several techniques for the registration (spatial alignment) of images from the same area have been proposed [2]–[5]. However, in the framework of oceanographic studies, the comparison of multitemporal and multisensor images is performed by the georeferencing of each image into a same geographic projection. Image georeferencing is the double process of correcting the remotely sensed image and transforming it into a known geographic projection (map coordinates). This way, multisensor data georeferencing enables comparison and fusion of information from different sensory modalities, which often provide complementary information about the region surveyed. For a good overview of existing methods for geometric correction of satellite imagery, the reader is referred to [1] and [6]. In these works, there are several models of varying complexity, with a variable accuracy. To achieve the desired accuracy of errors of less than one pixel, an additional step is commonly applied, using ground control points (GCPs), e.g., unique geographical locations or features such as small islands, lakes, capes, etc., for each of which the location in the image can be identified and the location on a map is known. GCP manual selection is extensively used in practical applications [1], [6]. However, there is a critical need to develop automated techniques requiring little or no operator intervention to georeferencing multitemporal and/or multisensor images when higher accuracy is desired. Toward this goal, feature-based methods, typically used in image registration, are more robust and suitable than area-based techniques [6], the later become unreliable when images have multiple partial or total occlusions and their gray-level characteristics vary. These techniques extract and match the common structures from two images, using region boundaries and other strong edges as matching primitives [2]-[5]. An input image is a sensed image (obtained by the satellite sensor), atmospherically corrected, and it has been coarsely georeferenced only using an orbital prediction model. We then obtain the contours following the coastline. The reference image is a map in a specific projection containing the sea–land boundaries present in a geographical area [7]. These sea–land boundaries will be referred to as reference contours. All the contours are then codified with a modified Freeman Code [4], and become the features used to identify matching structures in both images. We use the cross correlation matrix on the codified contours, but using the wavelet transform domain on each coded contour, moreover ensuring a robust matching. Once we have paired the contours we use a Dynamic Time Warping (DTW) technique [8], to pair and select the GCP allowing an elastic matching on the contour points. Afterwards we estimate the affine transform coefficients minimizing the error on matching GCPs. And finally the inverse transform on the working image using a nearest neighbor interpolation on the data gives the georeferenced image.

2. Results and discussions

Applying this method to an image with a slightly different projection than the reference, with a rotation and with clouds occlusions (forced synthetically), like the one on Fig. 1, we obtain the GCPs pairing of Fig.2 and the georeferenced image in Fig. 3.

To measure quantitatively the accuracy, we used the mean distance between the contours in the reference image and the contours on the georeferenced coastal image, distm< 1.37. Better than distm= $\sqrt{2}$, value when the distance between the contours is 1 pixel.

3. Conclusions

In these preliminary tests the method seems robust to rotations, clouds occlusions and slight variations on projections between the image and the reference.

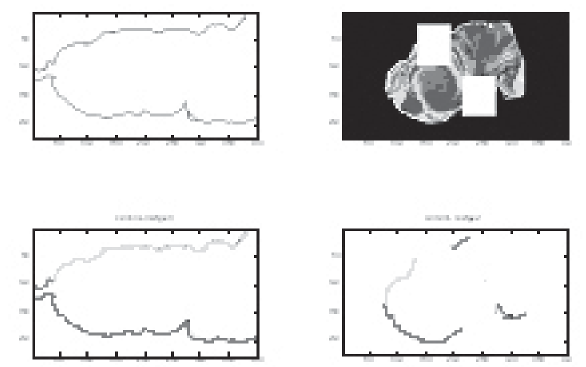

Figure 1. Multimodal images (up): GEBCO reference[7] (left), SST image rotated with synthetic clouds (right), and their respective coastline contours (down)

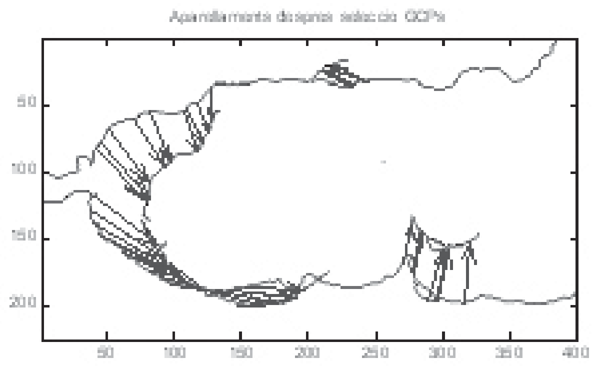

Figure 2. GCP pairing in both contour images.

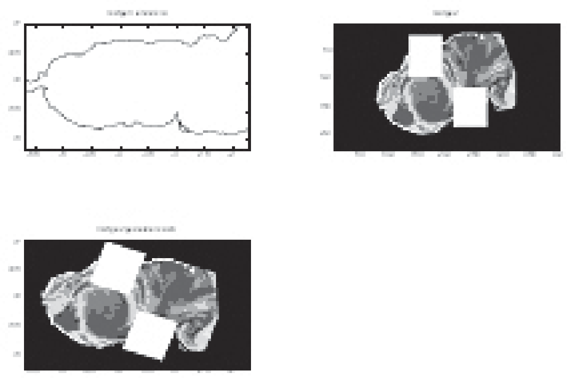

Figure 3. Original images and final georeferenced image.

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