of resting the TFK filtered data from the original one. It has been done this way to demonstrate that there is no problem of amplitude.
The second example, fig. 2(a), contains three waves, two of which with the same frequency. As can be seen on fig. 2(b), the f-k does not allow to distinguish between the two waves with the same slope. However a TFK is perfectly able to filter just one of them, fig. 2(c).

4 Conclusion

A time dependent f-k filter has been presented. It allows to filter seismic waves which are time varying and to distinguish between signals of the same frequency but at a different time. Some synthetic examples have shown the efficiency of the method.
This method should be useful for instance to remove water reverberations from OBS data without removing other seismic signals with trajectories which sometimes share the gradients.

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A MODEL-BASED EXPANSION ON INTERPOLATION FOR MULTIRESOLUTION SPARSE DATA

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Abstract

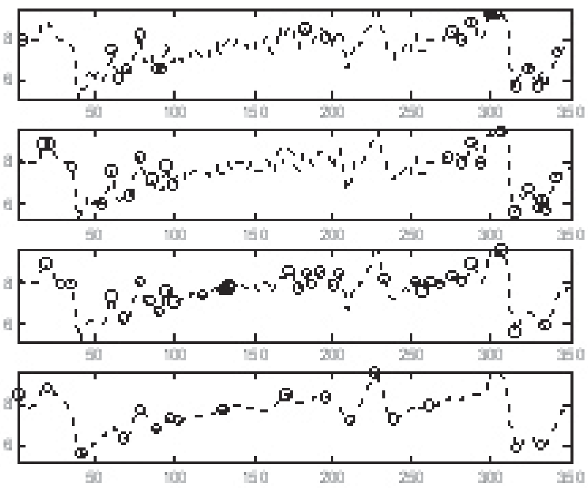
This paper addresses the interpolation of sparse irregular data when these sparse data belong to different scales. We propose an algorithm to iteratively approximate the intermediate values between irregularly sampled data, when a set of sparse values at coarser scales is known. This is possible if there is a characterized model for the multiresolution decomposition / reconstruction scheme of the dataset. Although the problem is ill-posed, and there are infinite solutions, this approach gives an easy scheme to interpolate the values of a signal using all the information available at different scales. This reconstruction method could be used as an extension on any interpolation. A simplified one-dimensional case illustrates the explanation; the scheme is based on a fast dyadic wavelet transform and its inversion, using a filter bank analysis/synthesis implementation for the wavelet transforms model. This can be a basis method suitable for applied cases where there are sparse measures from different instruments that are sensing the same scene simultaneously with several resolutions. Extensions of the method to sparse multiresolution data with higher dimensions (images or vector fields) also offer some promising preliminary results.

1. Introduction

In many signal processing applications it is necessary to reconstruct a signal from a set of sparse data, [1]-[3] to name a few. Many approaches have been used for sparse data interpolation, from the popular polynomial methods or splines, to other transform-based approaches such as zero padding, wavelet transform methods [4], regularization methods like WIPE or CLEAN deconvolution [5]. All these methods either make some assumption or put some restrictions on the data. This paper addresses the interpolation of multiresolution sparse, without any restriction on sparsity distribution of known data, and any condition on gap sizes or their distribution. Initially a filter model for the generation of multiresolution data and their synthesis counterpart is the main requisite, although finally this assumption can be partially relaxed, needing only the low pass component. To fix intuitively one possible application of the method we can take a remote sensing application in oceanography, and suppose we have a set of discrete measures (i.e. sea surface temperature, SST) obtained simultaneously by processing the obtained data from several instruments on different platforms (i.e. airborne, orbital). These datasets will have different spatial resolutions, and the occlusions (i.e. due to atmospheric factors, i.e clouds) will produce gaps between the discrete values. We would like a method to calculate, using these heterogeneous and discrete measures, the best match to the "real" SST map at the highest resolution that can be achieved by these sensors. Our approach takes advantage of an initial interpolation and a second step that iteratively refines the result, minimizing the error at the coarser scales. The method is an extension of the wavelet based reconstruction of nonuniformely sampled data in [6] to a multiresolution sparse data set. The zero crossings and the modulus maxima values of the wavelet transforms to reconstruct signals [7], or the edges on images, are also necessary references to our approach. The main difference is that, in our case, sparse data are in the 'data' domain at different resolutions, the low-pass components of the wavelet decomposition, opposed to [7], where sparse data are in the 'transform' domain. This difference makes our approach a priori more suitable for the cases when we have measures from instruments working simultaneously at different resolutions.

2. Results and Discussion

We represent our initial multiresolution sparse data, derived from a discrete vector in Fig. 1, where sparse multiresolution values are circles, and with less than 10% of the data at each dyadic wavelet decomposition level.



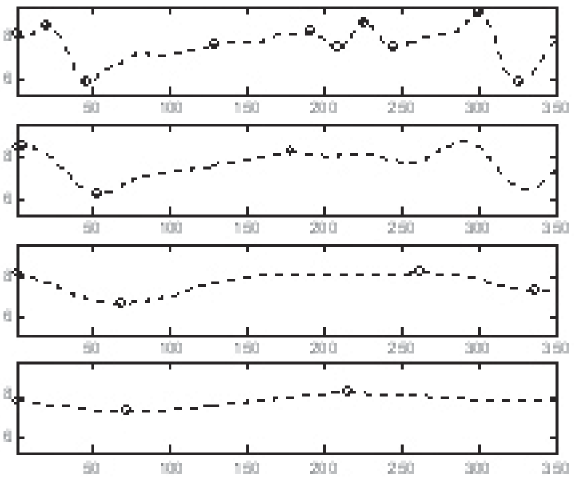


Figure 1. Unidimensional multiresolution sparse dataset, from level -1 to 6.

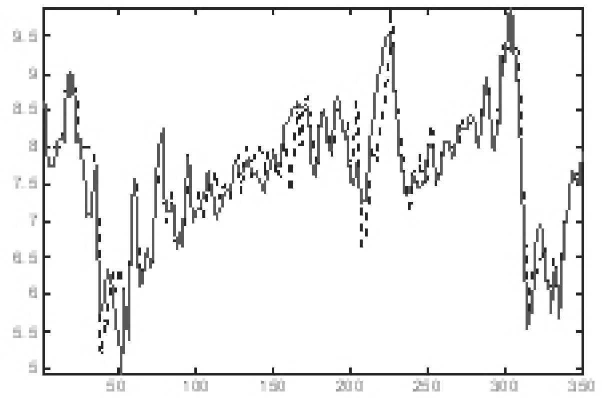


Figure 2. Reconstruction using CLEAN interpolation and 15 iterations on our method (continuous line) and original vector v (dotted line).

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,

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

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.