TELE - MONITORIZATION OF A SHIP CONDITION BASED ON SIGNALS SUPPLIED TROUGH AN AUTOMATIC INTEGRATED SYSTEM

Jose Antonio Casla Luzuriaga (1), Miguel Angel Gomez Solaeche (1), Julián Vergara Moro (2)

1. University of the Basque Country UPV/EHU, Navigation and Marine Engineering Department
2. Ingeoman S.L.

The research will focus on the development of advance monitorization technologies oriented to asses / evaluate the ship condition by means of IAS data and ship/shore and shore/ship communications.
This monitorizacion will be applied to re-engineering, operation and proactive maintenance of the ship.
The tele- monitorization is divided into four main blocks: TLX, TLY,TLZ and TLG.

TLX Telemetric System for ship-shore communication
TLY Communications server for recording and storing data in a Data Base
TLZ Data analysis for monitorization an predictive maintenance applications
TLG Data transmission from the analysis unit to final system users (shipyards, ship- owners, equipment manufacturers, crews, etc..)

g System Units and Functions
TLX Is divided into two subsequent blocks. TLXAD and TLCOM

TLXAD:
Gathers digital and analogical data values from different sources on board.
Data capture is achieved by connecting to the local net the IAS (Integrated Automatic System)
Compiled data is processed, normalized, prepared in packs, and delivered to TLCOM, for later transmission.

TLXCOM:
Actives the communication system if it is not in the permanent active modality and transmits to TLY the data packages received from TLXAD.
The connecting and transmitting frequencies to send the data packages ashore are independent of those frequencies used by the TLXAD to communicate with the ship´s IAS, in sampling and data capture operations.
The communication with the server TLXSRV is trustworthy with acknowledgment of the data transferred. TLCOM deals with re-tries in case of errors or impossibility of communication.
TLXCOM receives , as asynchronous signals from shore TLXSRV, reports and instructions. By these instructions TLX can increase or diminish the amount of data to be compiled from the IAS or its resolution, and also tune to the connection frequency or alternative routes for the transmission of data.

TLY A shore based TLXY server (Ingeoman Office), which receives data from the different TLXCOM,S records and stores the information in a data-base.
Initially, this data-base is used for verifying the system and establishing a prototype first level of vigilance for the ship subsystems.
TLZ Establishes de algorithms, correlations and logics to watch the functioning state of the ship different subsystems
These algorithms are based on the concepts of statistical distances and orthogonal decompositions
The last level of TLZ consists in an expert system which detects anomalies predicts breakdowns and makes a diagnosis of the originating causes. That is to say, a tool of Proactive and Predictive Maintenance
TLG The procedures to transmit the requested analysis data to final users have been already developed

g Ship-Shore Communications
Ship-shore communications are Internet communications of the IP type
Connection and Internet access from the ship is achieved by satellite communications in order to get the global coverage required to keep in contact the ship with the TLXSRV any time, anywhere.

A TIME DEPENDENT F-K FILTER

C. Simon[a], S. Ventosa[a], M. Schimmel[b], JJ. Dañobeitia[a], A. Mànuel[c]

[a] Marine Technology Unit, CSIC, Barcelona, SPAIN. Email: csimon@cmima.csic.es
[b] Institute Jaume Almera, CSIC, Barcelona, SPAIN
[c] CTVG, UPC, Vilanova i la Geltrú, SPAIN

1 Introduction

The particular characteristics of seismic wave propogations call for the development of special approaches in signal processing. Seismic data are recorded from a set of seismometers. They are usually represented on a so-called record section which takes advantage of the lateral coherence between neighbour traces. The x-axis represents the distance between the seismometers while the y-axis represents the time. One of the most usual techniques to identify and separate coherent waves is the f-k filter, [3]. It consists of a 2D Fourier Transform (FT) followed by some selection filter. The 2D FT allows to pass from the time-distance domain to the frequency-wavenumber one. It is particularly adapted for signals which propagate at constant velocity. However, the characteristics of seismic signals often vary with time and make impossible an efficient use of the f-k filter. On the other hand, if two signals arrive at a different time but at the same frequency and velocity, they won't be distinguished by this method. Thinking of the time-varying specificity of geophysic signals, we propose to adapt the f-k filter using a time-frequency spectral localisation method, called the S-transform.

2 The S-transform

The S-transform (ST) bridges the gap between the short time FT (STFT) and the wavelet transform. Like the STFT, the ST uses a window to localise the complex Fourier sinusoid but, unlike the STFT, the width and height of the window scale with frequency in analogy with wavelets. The ST of a time series is defined as [2]:

$$S(\tau, f) = \int_{-\infty}^{\infty} u(t) w(t-\tau, f) \mathrm{e}^{-2i\pi f t} \mathrm{d}t$$

where the most usual chosen window w is Gaussian:

$$w(t,f) = |f| / \left(k\sqrt{2\pi}\right) \mathrm{e}^{-2i\pi ft}\, \mathrm{d}t$$

in which f is the frequency, t and   the time variables and k a scaling factor which controls the number of oscillations in the window. The Gaussian window has a frequency-dependent variance: .

$$\sigma^2 = k^2 / |f|^2$$

The ST is perfectly invertible [1].

3 Time dependent f-k filter

As mentionned in the introduction, the f-k transform (FK) consists of a 2D FT. So, if we call h(t,x) the function representing a record section, its FK is: H(f,t) = FTx{FTt[h(t,x)]}. Now, to keep the time information of the record section, we propose to modify this transform in the following way:

So we pass from a 2D representation to a 3D one and get our time dependent f-k filter (TFK).

3.1 Application of the TFK

We perform our method in various steps:
1. Apply an f-k transform on the original data.
2. Select the areas of interest on the FK.
3. Apply a TFK on the original data but only on the frequency and wavenumber ranges of interest to simplify the procedure.
4. Compute the 3D filter, depending on the areas that should be kept or filtered.
5. Invert the TFK through an inverse ST and an inverse FT.

3.2 Results

We present two sets of examples. The first one, fig. 1(a), represents two hyperbolae with noise. An f-k filter would be unable to filter one of them as the velocity (slope) is time-varying. Moreover, both hyperbolae start with the same slope. Fig. 1(b) represents the positive frequency part of the f-k. It can be seen that it is impossible to differenciate one wave from the other one. Fig. 1(c) is the result

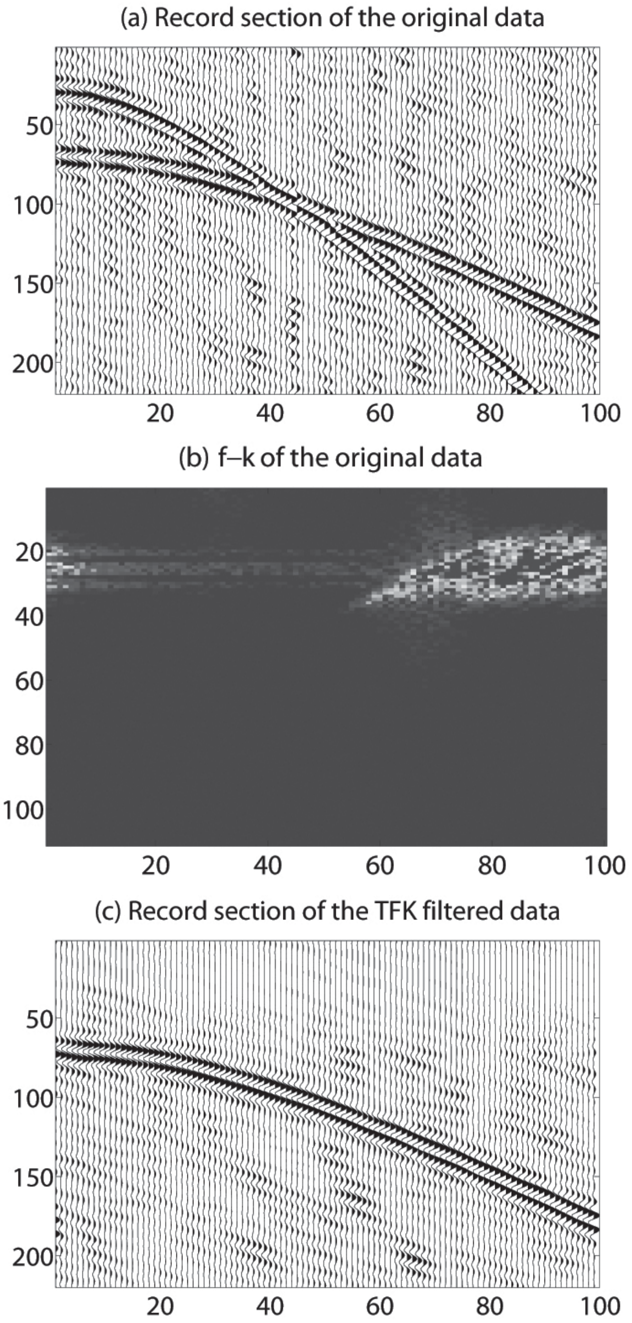

__Figure 1: Filtering a hyperbola using a TFK__

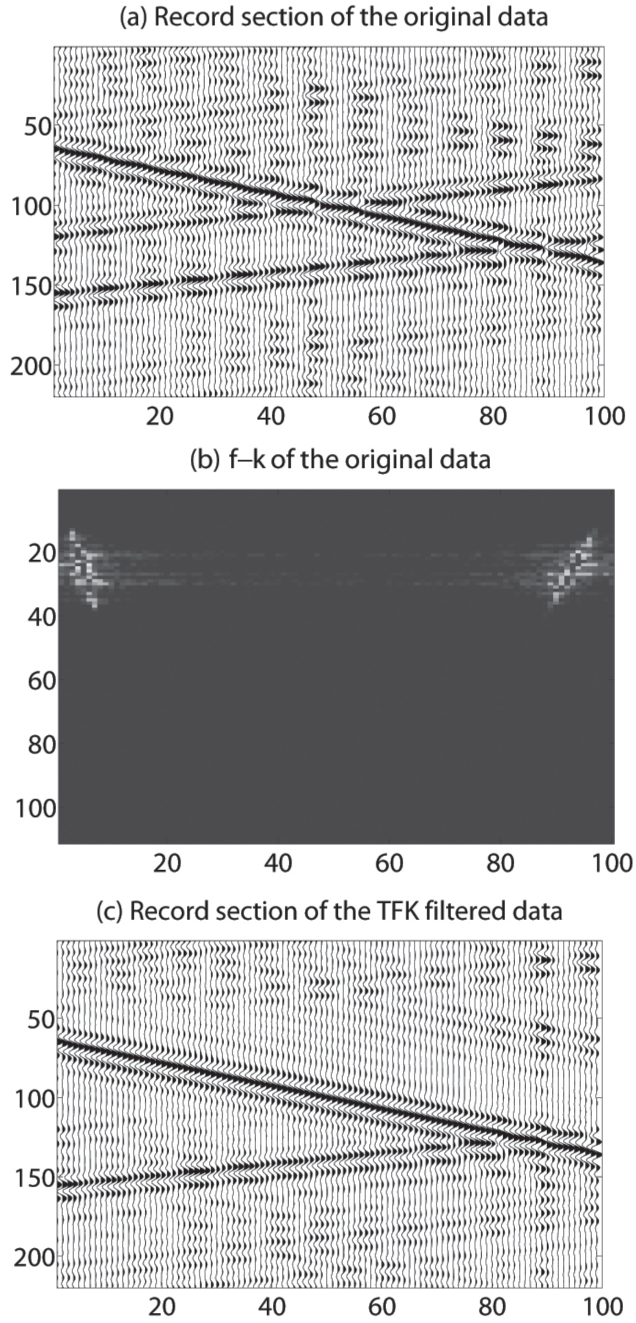

__Figure 2: Filtering a straight line using a TFK__

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.

References
[1]C. Simon, S. Ventosa, M. Schimmel, JJ. Dañobeitia, and J. Gallart. The s-transform and its inverses: side effects of discretising and filtering. 2006.
[2]R. G. Stockwell, L. Mansinha, and R. P. Lowe. Localization of the complex spectrum: The s transform. IEEE Trans. Signal Processing, 44(4):998–1001, 1996.
[3]O. Yilmaz and S. M. Doherty. Seismic data analysis: processing, inversion, and interpretation of seismic data. SEG, 2001.

A MODEL-BASED EXPANSION ON INTERPOLATION FOR MULTIRESOLUTION SPARSE DATA

Ramon Reig (1), Vicenç Parisi (2), Emilio García-Ladona (3), Pere Martí Puig (1)

(1) Codesign Hw/Sw Group (UVIC), C/de la Laura, 13, 08500 Vic, Barcelona, Spain
(+34)938861222 ramon.reig@uvic.cat, Vicenc.Parisi@upc.edu, emilio@icm.csic.es
(2)AHA -DEE (UPC), Av. Víctor Balaguer s/n, 08800 Vilanova i la Geltrú, Tarragona, Spain
(3)ICM -CMIMA (CSIC), Passeig Marítim de la Barceloneta, 37-49, 08003 Barcelona, Spain

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.