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SEABED CLASSIFICATION USING SUPERVISED FUNCTIONAL DATA ANALYSYS TECHNIQUES

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Javier Tarrío-Saavedra[1], Noela Sánchez-Carnero[2], Andrés Prieto[1]

[1]Departamento de Matemáticas, Universidade da Coruña, Spain, javier.tarrio@udc.es, andres.prieto@udc.es
[4]Centro Para el Estudio de Sistemas Marinos (CESIMAR). Centro Nacional Patagónico (CENPAT-CONICET). Argentina, noelas@gmail.com

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ABSTRACT
The objective of this work is the numerical analysis of the discretization parameters used in the functional statistical methodologies, on which the supervised classification for the automatic identification of seabed types in coastal zones is based. This methodology uses acoustic data obtained by a simple beam echo sounder (at 38kHz) coupled to a small boat. Each of the acoustic intensity curves has been previously preprocessed by applying time, power and ping length corrections in order to eliminate its dependence on depth. The experimental data were obtained in a controlled environment in the region of Cabo de Palos (Murcia, Spain), studying three different types of bottom: sandy, sandy with vegetation and rock. The statistical techniques applied to this particular case belong to the group of supervised classification techniques but combined with functional data procedures. The numerical results obtained and its analysis confirm that the use of a low number of elements of the discrete basis combined with their accurate approximation properties provide a correct classification of the three types of seabed considered.

RESUMEN
El objetivo de este trabajo consiste en el análisis numérico de los parámetros de discretización usados en las metodologías estadísticas funcionales en las que se basada la clasificación supervisada para la identificación automática de tipos de fondos marinos en zonas costeras. Para ello se parte de datos acústicos obtenidos mediante una ecosonda de haz simple (a 38kHz) acoplada a un barco de pequeñas dimensiones. Cada una de las curvas acústicas de intensidad ha sido previamente preprocesada mediante la aplicación de correcciones de tiempo, potencia y longitud de ping, con el objeto de eliminar su dependencia con respecto a la profundidad. Los datos experimentales han sido obtenidos en un ambiente controlado en la región de Cabo de Palos (Murcia, España), estudiándose tres tipos diferentes de fondo: arenoso, arenoso con vegetación y roca. Las técnicas estadísticas aplicadas a este caso particular pertenecen a la clasificación supervisada a partir de técnicas de datos funcionales. Los resultados numéricos obtenidos y el análisis de los mismos confirman que un bajo número de elementos de las bases de discretización usadas combinado con precisión en las aproximaciones de las mismas, proporcionan una clasificación correcta de las tres clases de fondos marinos considerados.

1. INTRODUCTION

Underwater acoustics represents one of the best methodological approaches for the study of the seabed [1]. The acoustic signal is a longitudinal wave which, in a fluid medium such as sea water, is transmitted at high speeds (around 1500 m/s) and long distances before being attenuated below ambient noise. Consequently, its use and analysis allows to work at large depths. In scientific echo sounders, this signal, generated by a transducer, propagates to the bottom in a three-dimensional waveform (whose shape depends on the directivity pattern of the transducer). Upon reaching the bottom, the acoustic signal is reflected by the seabed, first vertically, due to the main lobe, and immediately after, obliquely, due to the side lobes and the three-dimensional shape of the wave front (see [2] for a detailed discussion).

In pioneering applications of acoustic methods for the study of the seabed in the 1980s [3], the total energy was integrated within each of these curves (first and second echo) to perform an unsupervised classification of each of the points sampled [4]. With this methodological approach, good results were obtained [5], although the level of simplification (the whole curve characterized by two single variables) limited the classification obtained. In order to capture more information present in the acoustic curves, there were later multivariate approximations that extracted variables based on different types of signal analysis: Fourier analysis, energy integration, power distribution along the echo, etc. Despite these approaches drastically increase the number of variables from the initial approach, by describing the signal by a collection of variables, not always totally independent, with the potential drawback of discarding a relevant part of the information relating to the shape of the echo. Recently, the authors have recently proposed classification alternatives using techniques of Functional Data Analysis (FDA) [6], line of research followed in the present work.

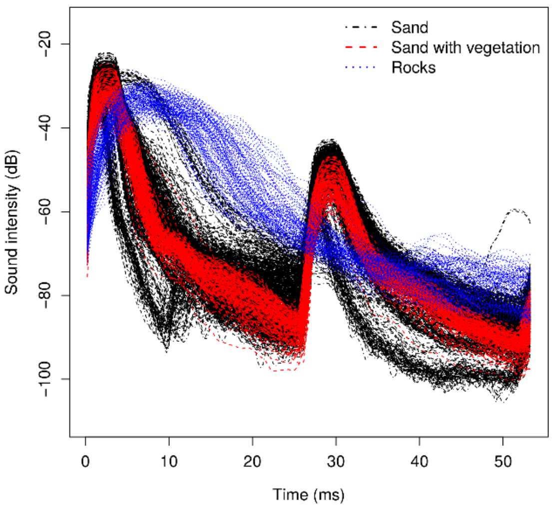

Figure 1. Preprocessed acoustic intensity curves plotted with respect to the time, including the first and second echoes. Each line style and color corresponds to a different class of seabed (sand, sand with vegetation and rocks).

2. DATA ACQUISITION

A beam echo sounder (EA400P Simrad) coupled to a 5m boat has been used in the experimental measurements. The acoustic intensity curves correspond to a frequency of 38 kHz and they were obtained in a controlled area of Cabo de Palos (Murcia, Spain), on July 19, 2014, where three different classed of seabed have been identified: sand, sandy bottom with sparse vegetation, and rocks. In order to eliminate the effect of depth, time corrections have been applied (echo lengthening with depth), power (wave attenuation with distance) and ping length (echo deformation due to it) through convolution using a kernel function that compensates the relation between pulse-length and depth [7]. All the corrections described above have been implemented using the ECOSONS software [8]. As a result, for each ping an acoustic intensity curve is obtained as a function of time, including two echoes or peaks, the first more related to the roughness of the background, while the second with its hardness [4]. In summary, the dataset consists in 1196 curves (see Figure 1), where the acoustic intensity have been recorded (in dB), one for each ping (678 for the first class, 236 for the second one and 282 for the third one), with acoustic intensity values integrated in 710 different times. Additionally, the values of the true seafloor classes are collected by direct inspection.

3. SUPERVISED CLASSIFICATION USING FUNCTIONAL DATA TECHNIQUES

Classification techniques can be grouped with respect to two different perspectives: (i) supervised classification techniques, where the seabed class (qualitative random variable) is estimated from a statistical model, whose parameters should be also estimated by means of a training sample (previously known the number and type of existing classes); and (ii) unsupervised classification techniques or cluster approaches, which allow the grouping of seabed classes according to different criteria of similarity. In the present work, only supervised classification have been taking into account. However, a more complete study comparing supervised and unsupervised functional data classification is under current research (see [6] for further details).

2.1 Functional data techniques

Time series data recorded on a fine grid of time points can be understood as realizations of a functional process, focusing the statistical analysis of the functional character of those data curves. Considering the data sample $\{X_i(t) : t = 1, \ldots, T\}$, with $i = 1, \ldots, n$ as a collection of curves, being each curve a single data, supervised and unsupervised classification algorithms can be applied. In particular, a variety of supervised classification techniques has been introduced and implemented in [9]. In this functional setting, a response variable (seabed type) is observed and this variable can be considered as the response of a functional generalized linear model (FGLM): a discrete response explained by a linear predictor on a functional variable $X(t)$, thanks to a link function, which depends on the logistic function. The FGLM technique assumes that there exists an underlying linear predictor, depending on a discrete set of functional coefficients.

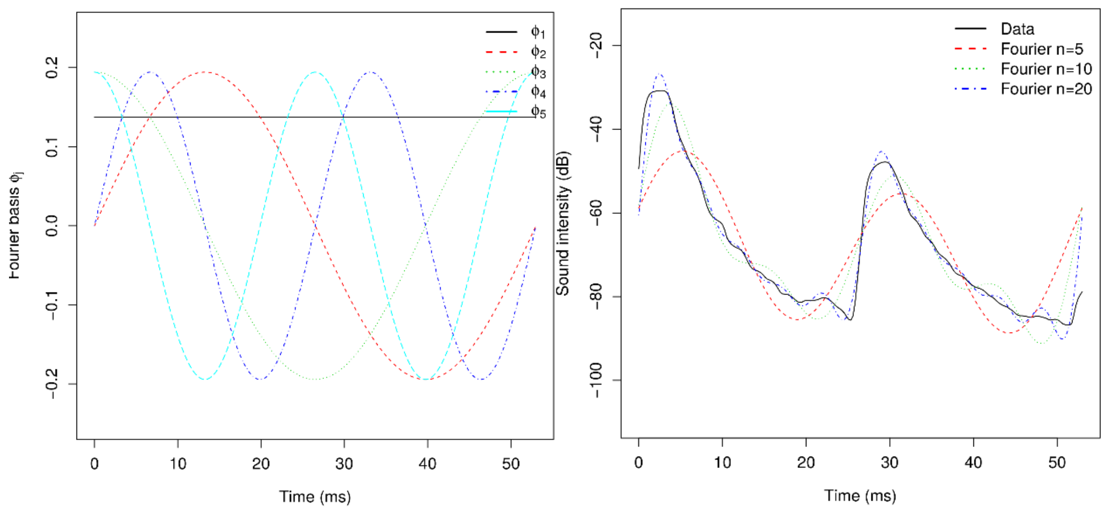

Figure 2. Fourier basis of 5 elements (left plot) and the approximation of an acoustic intensity curve based on its projection using a Fourier basis of 5, 10 and 20 elements (right plot).

However, there exists a more flexible approach: the functional generalized spectral additive (FGSAM) model, where a spectral decomposition of the covariance operator of $X(t)$ is applied. This technique remains labelled as "spectral" despite other type of non-spectral bases for discretization purposes are being utilized. In any case, both FGLM and FGSAM techniques require a discrete basis representation of the functional data available for classification. The most common bases are B-splines [10], Fourier (trigonometric) bases, functional principal components [11] or functional partial least-square bases. In the present work, B-splines bases, Fourier trigonometric bases, piecewise linear uniform basis, functional principal components and functional partial least-square bases have been considered.

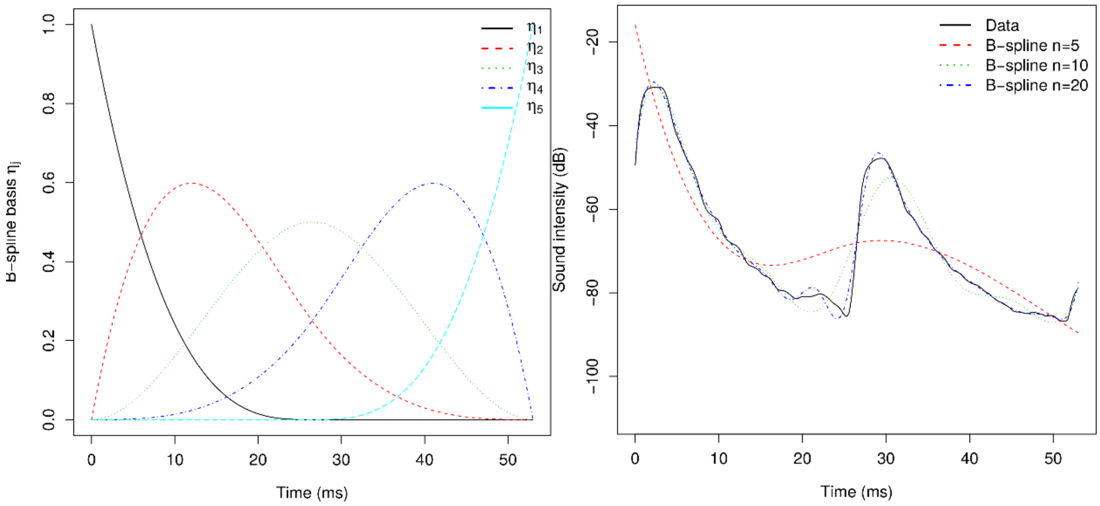

Figure 3. B-spline basis of 5 elements (left plot) and the approximation of an acoustic intensity curve based on its projection using a B-spline basis of 5, 10 and 20 elements (right plot).

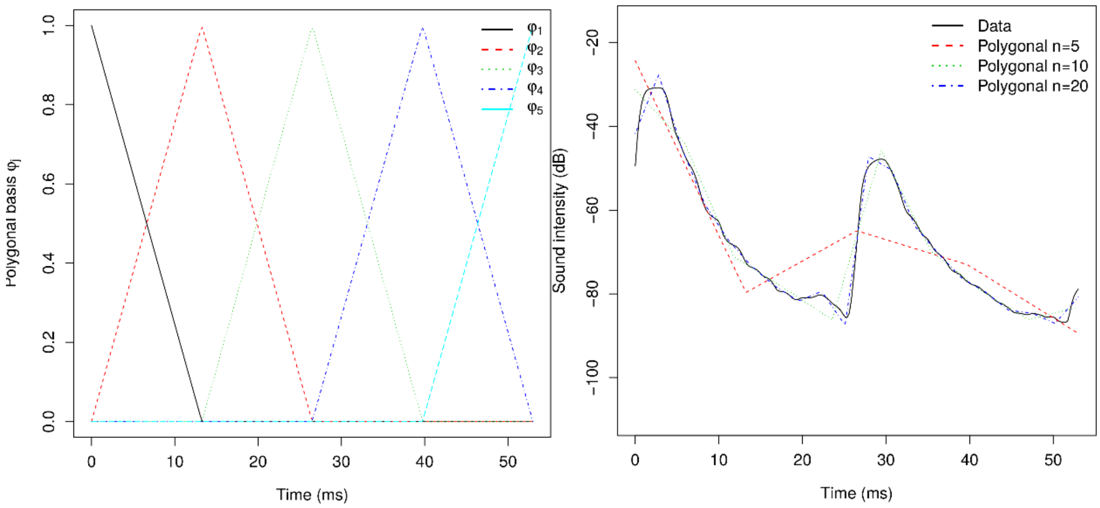

Figure 4. Local piecewise linear basis of 5 elements (left plot) and the approximation of an acoustic intensity curve based on its projection using a local piecewise basis of 5, 10 and 20 elements (right plot).

To illustrate the projection procedure necessary in the FGLM and FGSAM techniques, and its potential smoothing effects on the acoustic intensity signals, Figures 2-6 show a basis realization of five elements for each type of representation: B-splines, Fourier, piecewise linear, principal components and partial least-square bases, respectively. For every basis, each element of the basis is represented in the left plots. The right plots illustrate how an acoustic intensity curve is projected into these bases of five elements. In any of the bases selected for study, it is clear that increasing the number of basis elements causes a more overall accurate representation of the acoustic intensity signal. However, in the case of using a Fourier basis, since the acoustic curve is not periodic in time, the trigonometric approximation suffers from the well-known Gibbs phenomena, since the curve to be approximated is not periodically continuous at the end-points. Despite this lack of accuracy at the first and last time point, which could be read as a potential drawback for the supervised classification, the overall accuracy of the approximation on the tail of the first echo and the beginning of the second echo ensures a correct classification even for a Fourier basis.

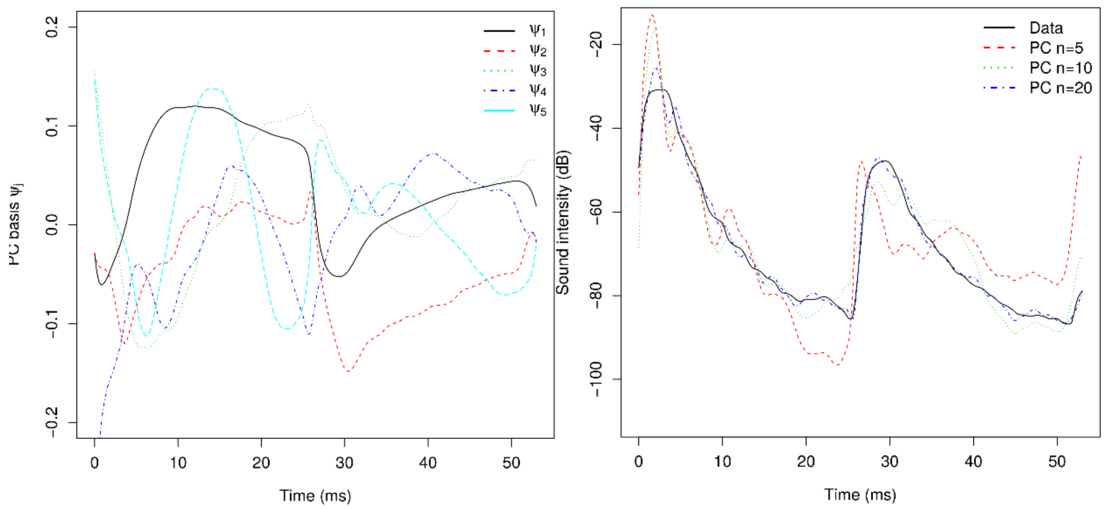

Figure 5. Principal component basis of 5 elements (left plot) and the approximation of an acoustic intensity curve based on its projection using a principal component basis of 5, 10 and 20 elements (right plot).

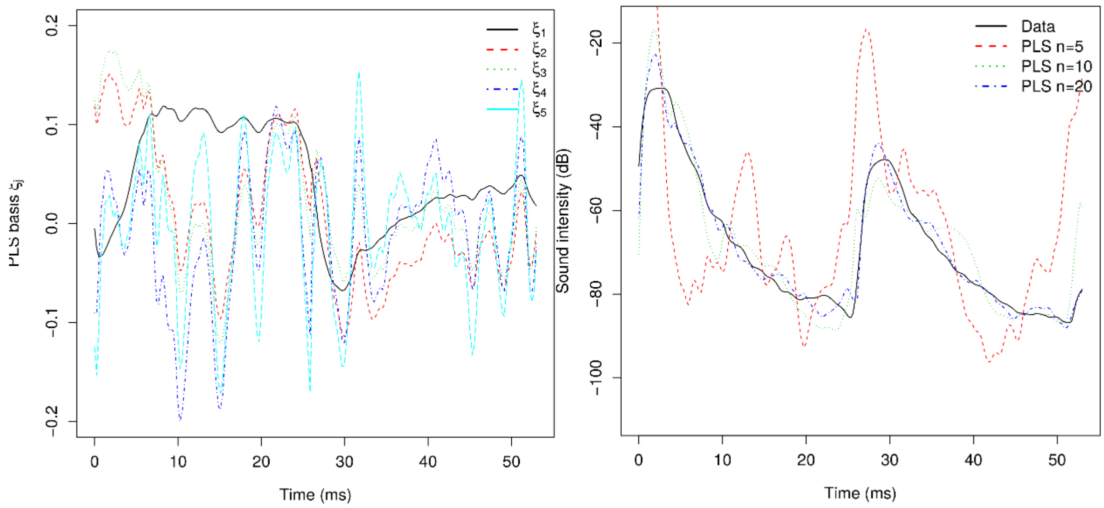

Figure 6. Partial least square basis of 5 elements (left plot) and the approximation of an acoustic intensity curve based on its projection using a partial least square basis of 5, 10 and 20 elements (right plot).

4. RESULTS AND DISCUSSION

To quantify numerically the effect of increasing the number of basis elements in the discrete representation of the functional data in the FGLM and FGSAM models, the supervised classification with both functional models have been computed considering B-spline bases, Fourier (trigonometric) bases, piecewise linear (polygonal) bases, principal component and partial least-square bases and varying the number of basis elements. Figures 7-11 show the boxplots and the means of the percentage of correct classification using these supervised functional techniques. The proportions of correct classification are computed by means of a 10-fold cross validation procedure (i.e., using for training the 90% of the acoustic intensity curves and the rest 10% of curves have been classified by using the functional FGLM and FGSAM models). In general, it can be observed that the FGSAM model provides slightly more accurate results than those ones obtained by using the FGLM model. It is also a common feature to all the bases considered in this study, the high accuracy of the supervised classification once more than five elements on each basis are assumed.

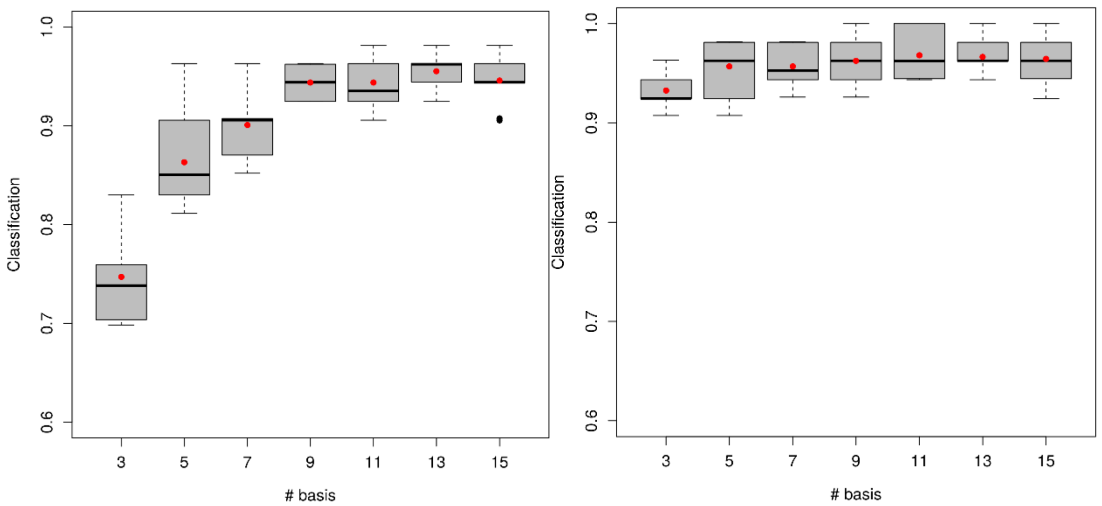

Figure 7. Boxplot and mean (red dot) of the percentage of correct classification using the supervised classification GLM (right plot) and GSAM (left plot) techniques, both based on a Fourier basis with different number of elements.

Additionally, the numerical results show a monotone increasing with respect to the number of basis elements. In every case considered, the maximum is reached after 5 or 7 elements are included in the bases. No significant differences are exhibited by the FGLM or FGSAM models in terms of median and dispersion of their percentages of correct classification: in both models the first and third quartiles have a similar behavior and the median and mean are close each other. Despite this similarity of the percentages of correct classification in all the bases that have been considered, it should be remarked that the computational efficiency is quite different among them. For instance, Fourier and B-splines bases have a similar performance (in terms of computational time taking into account the creation of the basis and their application in the classification procedures). However, the principal component bases and the partial least-square bases have a high computational cost (since they need to solve a linear eigenvalue problem involving the data curves in the former and to compute a least-square approximation taking into account the curves and the correct classification of the training data set in the latter).

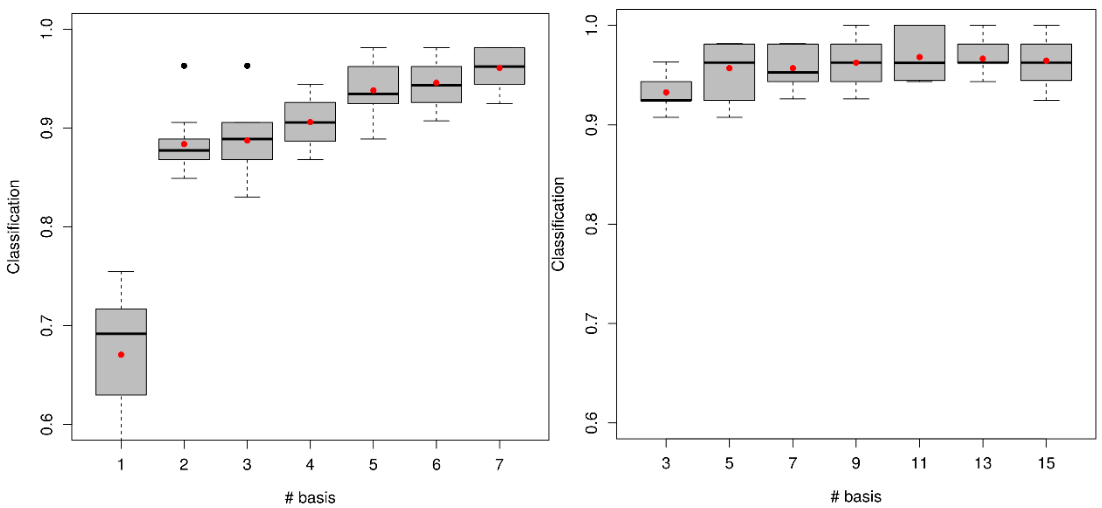

Figure 8. Boxplot and mean (red dot) of the percentage of correct classification using the supervised classification GLM (right plot) and GSAM (left plot) techniques, both based on a B-spline basis with different number of elements.

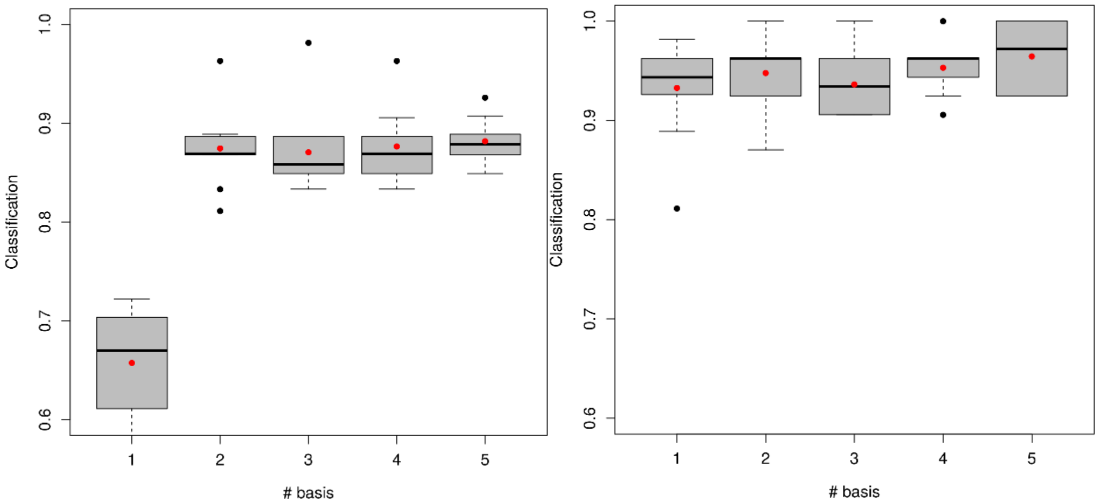

Figure 9. Boxplot and mean (red dot) of the percentage of correct classification using the supervised classification GLM (right plot) and GSAM (left plot) techniques, both based on a piecewise linear basis with different number of elements.

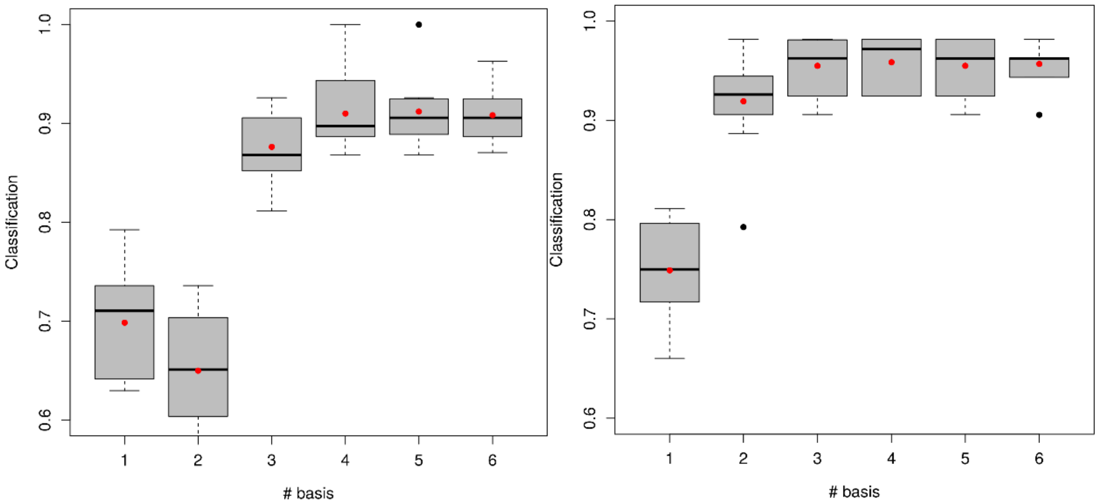

Figure 10. Boxplot and mean (red dot) of the percentage of correct classification using the supervised classification GLM (right plot) and GSAM (left plot) techniques, both based on a principal component basis with different number of elements.

5. CONCLUSIONS

It has been proposed to use supervised techniques for the classification of functional curves in order to identify the type of seabed from acoustic data provided by echo sounders. The proposed methodology provides an alternative for the automatic identification of types of seabed, with the advantage of not requiring a priori physical knowledge about the feature extraction of the acoustic intensity curves. In general, the correct classification percentage reaches values between 90-95% for all the bases considered in a range of a low number of elements used in each basis. This fact demonstrates the robustness of the proposed approach and guarantees accurate classification results even with a small base size in both FGLM and FGSAM models. In a further subsequently study, it will be provided functional supervised classification results for a variety of different cross-validation folds (this is, modifying the size of the training data set) and also those results derived from the unsupervised classification techniques but using, for instance, the classical multivariate k-means cluster methodology using the projection coefficients of these functional bases as input data. Such further numerical results will guarantee completely the robustness of an automatic and efficient classification of the coastal seabed.

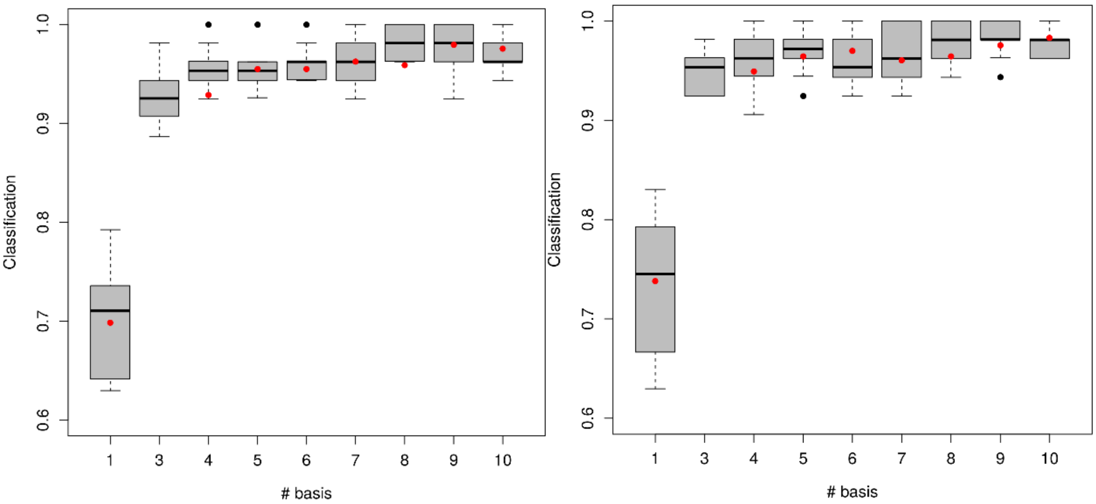

Figure 11. Boxplot and mean (red dot) of the percentage of correct classification using the supervised classification GLM (right plot) and GSAM (left plot) techniques, both based on a partial least square basis with different number of elements.

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