ATTRACTIVE TIME-VARIANT ORTHOGONAL SCHUR-LIKE REPRESENTATION FOR CLICK-TYPE SIGNAL RECOGNITION

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ABSTRACT

Analysis of click-type signals in the presence of noise with time-varying statistics is a challenging task, especially in low signal-to-noise ratio conditions. This well-known problem is commonly present in underwater passive acoustics applications. In this paper we present a novel solution for this dilemma as applied to marine mammal acoustics - a well-established basis for marine mammal study and protection. The adaptive orthogonal Schur-like algorithm is proposed to classify medium-frequency odontocete clicks. This technique is characterized by excellent convergence behaviour, very fast parametric tracking capability and robustness. The difficulty of recognition (classification) resides in the extraction of the signal's intrinsic information; i.e. extraction of an efficient signal signature. It is expected that the distances between the signatures within the class are minimal (small intra-class variance) and between the classes are maximal (high inter-class variance). This condition ensures a good recognition performance (separability of classes). The 2D signature proposed in this work and based on a selected set of the time-varying Schur coefficients assures this requirement. When compared to the classical Fourier approach, the proposed recognition method is four times as efficient for inter-class distances and twice as efficient for intra-class distances. The results of the recognition are given for sperm whale (*Physeter macrocephalus*) regular clicks and striped dolphin (*Stenella coeruleoalba*) *nacchere* clicks. They are very satisfactory and promising for other applications. The proposed technique can be easily implemented in real-time applications such as underwater acoustic monitoring systems.

RESUME

Les analyses des signaux du type cliquetis noyés dans un bruit dont les statistiques sont temps-variant est un challenge, surtout dans des conditions de rapports signal-sur-bruit défavorables. Cette problématique largement connue est couramment présente dans des applications de l'acoustique passive sous-marine. Dans cet article, nous présentons une solution novatrice appliquée dans le domaine de l'acoustique des cétacés qui actuellement constitue une base bien établie de l'étude et la protection des mammifères marins. L'algorithme orthogonal adaptatif de Schur est proposé pour classifier des clics de 2 espèces d'odontocètes. La technique introduite est caractérisée par une excellente convergence, un très bon suivi des paramètres et est robuste au bruit. Les difficultés de reconnaissance (classification) résident dans l'extraction de l'information intrinsèque du signal i.e. la mise en forme d'une signature efficace du signal. Il est attendu que les distances entre les signatures de la même classe soient minimales (petite variance intra-classe) et pour les différentes classes soient maximales (grande variance inter-classe). Cette condition assure de bonnes performances de reconnaissance (séparation des clases). La signature bidimensionnelle proposée dans ce travail et basée sur un ensemble sélectionné des coefficients temps-variant de Schur assure cette exigence. En comparant cette méthode avec l'approche classique de Fourier le gain d'efficacité est multiplié par 4 pour les distances inter-classe et par deux pour les distances intra-classe. Les résultats de la reconnaissance sont donnés pour les clics usuels de cachalots (*Physeter macrocephalus*) et les clics du type *nacchere* de dauphins bleus et blancs (*Stenella coeruleoalba*). Ils sont très satisfaisants et promettant pour d'autres applications. La technique proposée peut être facilement implémentée dans des applications temps-réel telles que des systèmes acoustiques de surveillance sous-marine.

1. INTRODUCTION

The click-type signal is characterized by short duration (microseconds to milliseconds), wide bandwidth (quasi flat spectrum), and is generally far from stationary. The processing of such a signal is a complex and challenging task, especially in low signal-to-noise ratio conditions. This becomes more difficult when the statistics of the background noise are time-varying. Click-type signal analysis requires signal processing techniques that fulfil the following principal conditions: robustness (to non-stationary noise), good time resolution (a click can last from tens to several hundred samples), efficient extraction of the signal's intrinsic characteristics (for detection, recognition, etc. purposes). A variety of methods are used for automatic recognition of transient signals. Some of them employ time and/or frequency representations. Other methods transform the signal to another space. These representations can be used for classification (e.g. template matching). Different parameters can be extracted for statistical classification. Many different classical (Fourier transform and its derivatives, parametric filters, time domain statistics) and advanced techniques (wavelets, Hilbert Huang Transform, High Order Statistics) are commonly used in processing of non-stationary brief signals, although not all are well suited for such processing. Classical temporal techniques use parameters such as duration, mean, variance, energy, amplitude, instantaneous phase, zero crossing rate or moments [16]. The bio-acoustics community widely uses Fourier based techniques and parameters such as principal frequency, bandwidth, cepstral coefficients or variations of the frequency or of the phase [17, 18]. Time-frequency representations are also used for signal description and classification [13]. The comparison of AutoRegressive (AR) modelling and the wavelet transforms as feature extraction tools is given in [19]. The use of neural networks for underwater signal processing is proposed in [20]. The chosen technique depends on the application and other factors such as implementation or budget issues. For example, for acoustic monitoring systems, real-time processing is paramount. Therefore it is expected that complex and time consuming methods would not be used, though there may be deterioration in performance.

In this paper we introduce the adaptive orthogonal Schur-like parameterization, a novel technique for analysis of brief acoustic signals. The adaptive Schur algorithm as shown in this paper is a powerful, low complexity technique that is also very easy to implement. A first study of this technique as applied to underwater passive acoustics is presented in [1]. This technique has already been applied to detection and analysis of sperm whale clicks [2]. This paper is an endeavour to classify mid-frequency marine mammal clicks.

The adaptive Schur algorithm is composed of two steps. First, recordings are analyzed to extract all non-stationary transients (detection of clicks) [2,7]. Secondly, the extracted clicks are assigned to different classes (recognition of clicks) [7]. We introduce a click-type signature that is based on a selected set of the time-varying Schur coefficients. The objective of this study is to recognize (classify) broadband acoustic transients emitted by two odontocete species, the sperm whale (*Physeter macrocephalus*) and the striped dolphin (*Stenella coeruleoalba*). The sperm whale regular clicks [3-5] and striped dolphin *nacchere* clicks [6] have very similar time and frequency characteristics; i.e. duration of a few milliseconds and a wide bandwidth [7]. These two odontocete species were chosen because they seem to represent the most difficult scenario for marine mammal click-type calls: similar duration and frequency bandwidths that overlap by more than 90% [7].

The clicks considered here are emitted in sequences. The principal parameter characterizing the sequence of clicks is the ICI (inter-click interval). This slow time-varying parameter defines the time distances between consecutive clicks within the sequence of clicks. Therefore, the recognition of such clicks can be carried out in two ways: by a global and a local approach. In this paper we consider the latter approach, which means that the classification is performed on every single click. This method is much more challenging than the global approach. In the global approach, the distinction between sperm whale regular clicks and *nacchere* striped dolphin clicks can be performed by exploiting the ICI, which is about 0.5-2 s for the sperm whale and about 0.1 s for striped dolphin. The problem appears when clicks are missing or when different click sequences overlap, making estimation of the ICI very complicated. The local classification approach applied to a sequence of clicks can be considered as a pre-processing step to the global classification approach (support for the ICI estimation).

In this paper, we give results of the recognition obtained on sperm whale regular clicks (called *Pma* clicks) and striped dolphin *nacchere* clicks (called *Sco* clicks). We discuss the performance and present perspectives.

2. MATERIAL AND METHODS

Sperm whale clicks were recorded in the canyon of Toulon (Mediterranean Sea, France) (42°58'N, 5°51'E, 42°39'N, 5°43'E, 42°39'N, 6°30'E, 42°58'N, 6°27'E) in August 2004 [8]. The recordings of striped dolphin clicks were made in the Ligurian Sea in 2002 [6]. Both recordings were performed with the omnidirectional hydrophone (0-30 kHz) towed at a depth of about 50-100 m. The acoustic signals were recorded with a 44.1 kHz sample rate and 16 bit resolution via a commercial audio PC card.

2.1 Adaptive Schur Algorithm

The adaptive Schur-like parameterization [9,10] was proposed for the recognition of the bio-acoustic clicks emitted by sperm whales and striped dolphins. More detailed discussion of this technique as applied to short-term stochastic signal processing is given in [7].

The adaptive Schur algorithm, also called the innovations filter or whitening filter, is in fact an optimal orthogonal linear prediction filter. At every time-instant the filter calculates an optimal value of the signal at instant t taking into account all its past values. The solution of the prediction is calculated from the orthogonal projection of the current signal on its past samples. The forgetting factor is introduced to weigh the past samples [7]. The filter is always stable numerically because all the signals within the filter are normalized to unity.

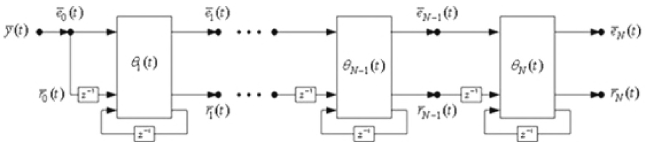

Figure 1. Adaptive orthogonal Schur filter

The ladder-form orthogonal filter is adaptive (in time) and recursive (in order) (fig.1, eq. (1)-(2)). The filter is composed of *N* identical sections $\theta_n(t)$ (the number defines the filter order) which are completely defined with second-order statistics by the time-varying Schur coefficients $\rho_n(t)$ (also called the reflection coefficients). The adaptive Schur algorithm is defined by the three following equations:

$$\begin{cases} \rho(n+1,t) = \rho(n+1,t-1)AB - e(n,t)r(n,t-1) \\ e(n+1,t) = CB^{-1}\left[e(n,t)+\rho(n+1,t)r(n,t-1)\right] \\ r(n+1,t) = CA^{-1}\left[\rho(n+1,t)e(n,t)+r(n,t-1)\right] \end{cases} \quad (1)$$

where A, B and C are as follows:

$$\begin{cases} A = \left(1-e^2(n,t)\right)^{1/2} \\ B = \left(1-r^2(n,t-1)\right)^{1/2} \\ C = \left(1-\rho^2(n+1,t)\right)^{-1/2} \end{cases} \quad (2)$$

The variables $\rho(n,t)$, $e(n,t)$ and $r(n,t)$ denote respectively the time-varying Schur coefficient, the normalized forward prediction error and the normalized backward prediction error on the *nth* section at the time *t*. The requisite number of sections depends on the signal type. This is closely linked to the signal energy distribution on the filter sections. As it was demonstrated in [7], the energy on the filter sections globally decreases as the number of sections increases. In practice the order of the filter is chosen between 10 and 20.

The signal $y(t)_{t\in\{1,\dots T\}}$ input to the filter is transformed into the 2D matrix $\mathbf{\Theta}_{NxT} = \left[\mathbf{\theta}_1,\dots,\mathbf{\theta}_N\right]'$ (see fig.1):

$$\mathbf{\Theta}_{NxT} = \begin{bmatrix} \rho(1,1) & \rho(1,2) & \cdots & \rho(1,\mathrm{T}) \\ \rho(2,1) & \rho(2,2) & \cdots & \rho(2,\mathrm{T}) \\ \vdots & \vdots & \ddots & \vdots \\ \rho(\mathrm{N},1) & \rho(\mathrm{N},2) & \cdots & \rho(\mathrm{N},\mathrm{T}) \end{bmatrix} \quad (3)$$

The matrix columns represent time and the rows represent order. In our work real-time processing is essential. Therefore we present the mathematical complexity of the algorithm in table 1. We also estimated the algorithm processing time for a 1 second signal sampled at 44.1 kHz as a function of the filter order (commercial PC: processor 1.6 GHz, RAM memory 1 GB). This relation is given in fig.2.

Table 1 – Mathematical complexity of the algorithm (number and weight of mathematical operations for time and order loops)

Operation	Number of cycles According to IEEE Standard 754	Number of operations Order loop *n*	Number of operations Time loop *t*
+ or -	1	6	3
*	2	12	5
√	5	3	1
/	5	3	1

The adaptive Schur algorithm has two loops: the major loop in time *t* and the minor loop in order *n*. The mathematical complexity of the algorithm for the minor loop is *O(N)* and for the major loop is *O(T*N)*. Due to recursive and adaptive processing the complexity is linear, which is very attractive for practical implementation.

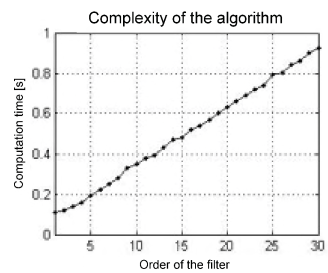

Figure 2. Computational complexity of the technique

This signal analysis is based on the matrix of time-varying Schur coefficients:

$$\Theta(n,t) = \left\{\rho(n,t): \quad n\in\{1,\dots,N\}, \quad t\in\{1,\dots,T\}\right\} \quad (4)$$

which reflect the second-order statistics of the filtered signal. They gravitate towards their optimal values when the signal is (quasi) stationary. When there is an important variation in the signal covariance, the time-varying Schur coefficients reflect these changes.

2.2 Recognition of click-type signals

Processing of the click-type signal is especially challenging due to its short duration and wide bandwidth. Classical methods for click-type signals analysis have difficulty capturing the signal's intrinsic information. There is a need for new techniques that are better suited for this task. Here, our method is appropriate for transient signal recognition. The analysis is based on the 2D Schur-like representation i.e. the set of time-varying Schur coefficients.

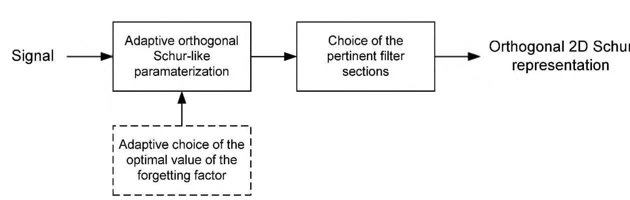

Figure 3. Generation of 2D orthogonal (Schur-like) signature

The recognition problem posed in this work is supervised, i.e. we use a specific set of click-type signal representatives for each class (sperm whale regular clicks ("clicks Pma") and striped dolphin *nacchere* clicks ("clicks Sco")). The proposed signature (pattern Sc_{TV} – Schur time-variant) of the click-type signal based on time-varying Schur coefficients is successful for discrimination (high inter-class variance) and invariance (low intra-class variance).

The signatures Sc_{TV} for both classes are calculated according to the method presented in fig.3 and are shown in fig.4. A random set of clicks for each class (sperm whale and striped dolphin) input to the adaptive Schur filter results in a set of the time-varying Schur coefficients (2D representation, see eq. (3) and fig.4). The signature Sc_{TV} is calculated as the mean of a set of patterns for that class. In our study we used 50 clicks chosen randomly from datasets. These sets are used for determining the most discriminating K Schur coefficients. First, for the two classes *Pma* and *Sco*, we calculate the vector of discrimination H_{1xN} :

$$\underset{i=1...N}{\forall} \qquad \mathbf{H}_{1xN}(i) = \left\| \rho_i^{Pma} - \rho_i^{Sco} \right\| \tag{5}$$

and with:

$$H(1) > ... > H(j) > ... > H(N) \xrightarrow{choice} \max_j (H)_{1xK} \tag{6}$$

Finally, we conserve K of the most unlike (between classes) Schur coefficients, which guarantee very good class separability. The signatures Sc_{TV} are calculated for three different frequency bands: low (LF, 1-4kHz), medium (MF, 7-10 kHz) and high frequency (HF, 12-16 kHz) bands. The signatures Sc_{TV} for sperm whale regular clicks (*Pma*) and striped dolphin *nacchere* clicks (*Sco*) for each of the three bandwidths are presented in fig.4.

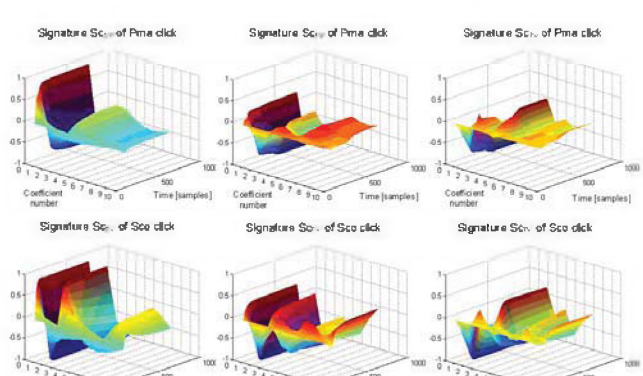

Figure 4. Signatures Sc_{TV} (2D) of Pma and Sco clicks First line is for Pma clicks and second line is for Sco clicks The signature Sc_{TV} is given for three different frequency bands (in columns): LF (1-4 kHz), MF (7-10 kHz) and HF (12-16 kHz)

For comparison purposes we decided to also evaluate the performance of a widely used classical recognition technique based on the Fourier technique. The Fourier signature is given as a set of 32 Fourier coefficients. The number of Fourier coefficients was chosen to capture the global spectral structure of the signal, and not local changes, which can be influenced by noise or propagation effects.

The signal description (recognition) aims to obtain the signature (pattern) that most effectively represents the signal. Ipso facto, it is expected to reach a high discrimination between classes and a high invariance of the signature within each class. In this work we proposed two supervised classification approaches:

- template matching,
- statistical.

For the first approach we use four different dissimilarity metrics: correlation coefficients, and Euclidian (d_E), Chebyshev (d_{Ch}) and Minkowski (d_M) distances, which are defined as follows (for two signals x and y):

$$d_E = \left\{ \sum_{i=1}^{p} \left(x_i - y_i \right)^2 \right\}^{1/2} \tag{7}$$

$$d_{Ch} = \max_i \left| x_i - y_i \right| \tag{8}$$

$$d_M = \left\{ \sum_{i=1}^{p} \left(x_i - y_i \right)^m \right\}^{1/m} \tag{9}$$

In the statistical approach, we proposed three parameters (variables υ_1, υ_2 and υ_3) calculated from the 2D Schur representations (fig.4):

$$\upsilon_1 = \rho_2(T) - \rho_3(T) \tag{10}$$

$$\upsilon_2 = \sum_{j \in \{7,8,9\}} \left(\frac{1}{T} \sum_{i=1}^{T} i \rho_j^*(i) \right), \quad \rho_j^* = \rho_j - \min\left(\rho_j(i)\right) \tag{11}$$

$$\upsilon_3 = \frac{1}{N} \sum_{j=1}^{N} \sum_{i=1}^{T} \rho_j^2(i) \tag{12}$$

These variables allow an almost perfect discrimination between sperm whale regular clicks and striped dolphin *nacchere* clicks. They were chosen *a posteriori* based on our two datasets.

3. RESULTS AND COMMENTS

The performance of the click-type signal recognition is obtained from two odontocete calls: sperm whale regular clicks and striped dolphin *nacchere* clicks. We present the similarities between these two categories of clicks in time and frequency domains for LF, MF and HF bandwidths (see table 2).

Table 2 – Correlation results between sperm whale (Pma) clicks and striped dolphin (Sco) clicks in time and frequency domains for four LF (1-4 kHz), MF (7-10 kHz), HF (12-16 kHz) bandwidths and wideband (whole frequency range).

	LF band	MF band	HF band	Wideband
Correlation : click Pma – click Pma				
Time	0.421±0.12	0.411±0.10	0.391±0.12	0.264±0.09
Frequency	0.709±0.13	0.744±0.11	0.722±0.11	0.642±0.16
Correlation : click Sco – click Sco				
Time	0.459±0.14	0.316±0.7	0.29±0.08	0.368±0.12
Frequency	0.740±0.15	0.671±0.14	0.684±0.10	0.741±0.15
Correlation : click Pma – click Sco				
Time	0.311±0.09	0.320±0.07	0.318±0.07	0.201±0.06
Frequency	0.573±0.14	0.660±0.13	0.694±0.11	0.501±0.10

We note that neither in time nor frequency domains is it possible to propose a threshold for distinguishing these classes. First, this is due to the fact that both clicks classes have high variance within-class (we obtain low values of the correlation between clicks of the same species). This diversity results from the natural intrinsic richness of the clicks and from propagation effects. Secondly, the *Pma* and *Sco* clicks are very similar in duration and frequency band, and thus the values of the correlation between clicks of the two species are significant.

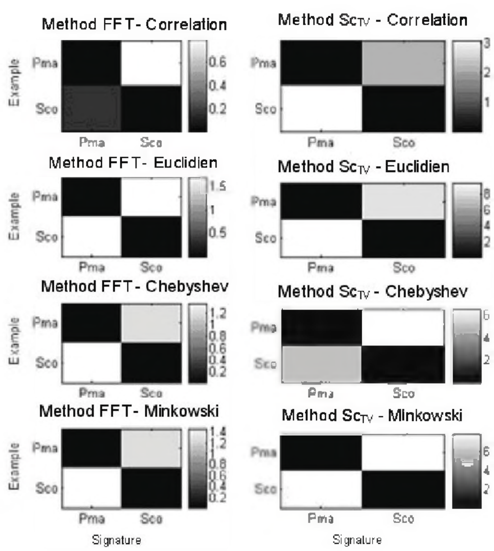

Figure 5. Classification performance for Pma and Sco clicks (mean values of intra- and inter- class distances in dB) The results are given for LF band (Template Matching)

The performance of classification by the template matching approach is given in fig.5-6. The patterns of each class are compared to the signatures *Pma* and *Sco*. The mean values of these intra-class and inter-class distances are given in fig.5. These values are normalized for each class to 0 dB for the intra-class distances. This means also that the inter-class and intra-class distances should be minimal. The distribution of values of the inter-class and intra-class distances is given in fig.6 (for the Minkowski metric). We note that the proposed signature Sc_{TV} ensures lower intra-class distances and higher inter-class distances, which results in a much improved discrimination performance. When compared to the performance of the Fourier based recognition technique, the proposed method is four times more efficient for inter-class distances, and twice as efficient for intra-class distances (see fig.6). The separability of clicks, which was impossible in the time and frequency domain, becomes attainable in the space of the time-varying Schur coefficients.

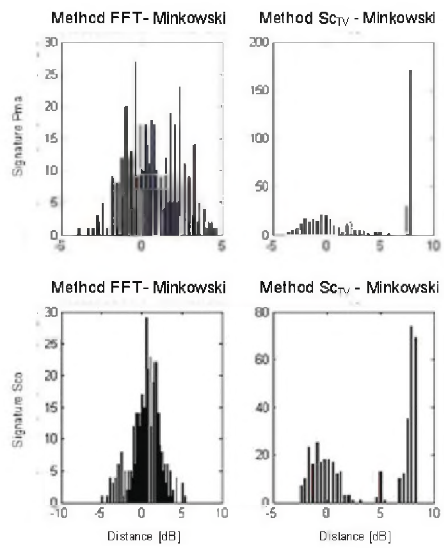

Figure 6. Histogram of intra- and inter- class distances for the Minkowski metric (Template Matching)

The parameters proposed in eq. (10)–(12) allow the accurate discrimination between sperm whale regular clicks and striped dolphin *nacchere* clicks (see fig.7). However, we note that these variables for sperm whale clicks (black in fig.7) are somehow correlated. This can be attributed to different diving phases of sperm whales. The classification results depend also from the performance of the data acquisition. This requires further research and analysis.

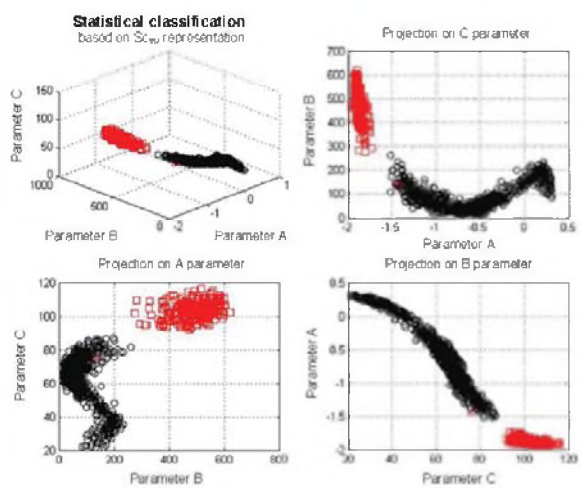

Figure 7. Statistical classification of Pma (black) and Sco clicks (red) in 3D representation space (parameters A, B and C correspond to variables υ_1, υ_2 and υ_3)

The correlation results shown in table 2 and the classification results based on the Fourier signatures (fig. 5) compared to the performance of the recognition method proposed in this paper let conclude that the two proposed recognition approaches, i.e. the template matching and the statistical classification based on the 2D orthogonal Schur-like representation, are very efficient and robust for underwater click-type signal analysis.

4. CONCLUSION

In this paper we presented a novel click-type signal recognition method based on the time-variant Schur algorithm. This orthogonal technique appears well suited for underwater signal processing. The adaptive and recursive nature of the proposed algorithm is very attractive for real-time processing. We proposed an efficient 2D signature for click-type signals. We evaluated our recognition method on sperm whale (*Physeter macrocephalus*) regular clicks and stripped dolphin (*Stenella coeruleoalba*) *nacchere* clicks. These two species clicks present some common characteristics that make classification quite challenging, especially for the classifier based on the Fourier transform. The recognition results showed that concerning classification performance and resistance to noise, the 2D Schur signature is considerably more efficient than the classical Fourier descriptor. Moreover, this signature is more compact and is characterized by a lower variability. Motivated by very promising results obtained from this study, we would like to investigate the proposed recognition approach on other marine mammal click-type and chirp-type calls. We are currently working on the issue of independence of the recognition algorithm from acquisition system set-up.

5. ACKNOWLEDGMENTS

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