

JUNE 02 2013

Odontocete click train deinterleaving using a single hydrophone and rhythm analysis **FREE**

Olivier Le Bot; Julien Bonnel; Jérôme I. Mars; Cédric Gervaise



Proc. Mtgs. Acoust. 19, 010019 (2013)

<https://doi.org/10.1121/1.4800655>



View
Online



Export
Citation

CrossMark

Related Content

Extraction of pulse repetition intervals from sperm whale click trains for ocean acoustic data mining

J. Acoust. Soc. Am. (January 2013)

Odontocete click train deinterleaving using a single hydrophone and rhythm analysis

J Acoust Soc Am (May 2013)

Optimized iterative decoding method for TPC coded CPM

AIP Conference Proceedings (May 2018)



ASA

Advance your science and career as a member of the
Acoustical Society of America

[LEARN MORE](#)



ICA 2013 Montreal
Montreal, Canada
2 - 7 June 2013

Animal Bioacoustics

Session 2aAB: Conditioning, Segmentation, and Feature Extraction in Bioacoustic Signals

2aAB7. Odontocete click train deinterleaving using a single hydrophone and rhythm analysis

Olivier Le Bot*, Julien Bonnel, Jérôme I. Mars and Cédric Gervaise

*Corresponding author's address: ENSTA Bretagne, Brest, 29200, Bretagne, France, olivier.le_bot@ensta-bretagne.fr

Most odontocetes live in pods of several individuals, resulting in an overlapping of click trains recorded by passive acoustic monitoring systems. Localization algorithms and click classifiers are usually used for train separation. However, their performances fall down if individuals are too close to each other or if acoustical parameters vary greatly from click to click, respectively. Assuming odontocete clicks follow rhythmic patterns, we propose to use a rhythm analysis to separate mixed click trains from a single hydrophone. The proposed algorithm is based only on inter-click-intervals (ICI) to cluster clicks into trains. It uses information given by complex-valued autocorrelation to compute a histogram which will exhibit peaks at ICIs corresponding to interleaved trains. By this technique, subharmonics corresponding to multiples of ICIs are automatically suppressed. The algorithm is then extended by a time-period analysis leading to a time-varying ICI spectrum. A threshold can be applied on this spectrum to detect the different interleaved trains. The final result is a binary time-ICI map on which trains can be fully and easily distinguished and extracted. We validate it on simulated and experimental data and we show that the algorithm is particularly suitable as a preprocessing tool prior to localization and classification schemes.

Published by the Acoustical Society of America through the American Institute of Physics

INTRODUCTION

One aim of passive acoustic monitoring (PAM) is to study cetaceans, whether to understand their sound production mechanisms, their behavior, ecology and the impacts of anthropogenic noise on their communications [1, 2, 3, 4, 5]. Several methods can be used for such monitoring as reviewed by Mellinger et al. [6]. Marine mammals mainly produce two types of sounds: tonal sounds and clicks. Both can easily be recorded by PAM systems. Here we focus only on clicks produced by odontocetes.

PAM systems usually record long time-series that require effective signal processing tools for fast and automatic analysis. The main problem when analyzing data acquired in natural fields is that recordings contain a mixture of clicks coming from several biotic or abiotic sources. Moreover, odontocetes are usually living in pods of several individuals, which leads to overlapping click trains from multiple individuals. Therefore there is a need to develop signal processing tools that sort out and separate multiple sources recorded at one single hydrophone.

Several methods performing click sorting based on acoustical parameters have already been reported in the literature [7, 8, 9]. However, most of these algorithms need prior training [10] and nearly invariant acoustic parameters [11] to work properly. This might be inconsistent with acoustical properties of recorded odontocete clicks that vary greatly depending on orientation changes of the animal relative to the hydrophone. In this communication, we propose to use the rhythm of the clicks, supposed nearly constant, to sort out and cluster clicks into trains. Indeed, odontocetes rarely emit isolated clicks but trains of several clicks following a certain rhythmic pattern characterized by the inter-click interval (ICI) [12].

Such a problematic has already been studied in other fields like automatic tempo detection in music or pulse train deinterleaving in radar. Most of the algorithms in these fields use the time of arrival (TOA) of the pulses and are based on an autocorrelation function of the pulse trains to build an histogram. Cumulative difference (CDIF) [13], τ -histogram [14] and sequential difference (SDIF) [15] are the most common ones. All of them have advantages and drawbacks. Their main disadvantage is that if autocorrelation function yields to produce peaks located at ICI-values corresponding to interleaved trains, it also produces peaks located at ICI-values corresponding to integer multiples of the fundamental ICIs. This can give results difficult to read and interpret. For this reason, [16] and [17] have introduced the concept of complex-valued autocorrelation function that almost completely suppress subharmonics of the autocorrelation while keeping peaks located at ICI-values of the interleaved trains.

Our main contribution is to use this complex-valued autocorrelation function to sort out clicks emitted by multiple clicking odontocetes. We also demonstrate that the proposed method can be adapted to track click trains whose rhythm changes according to the time. This leads to a time-varying ICI spectrum, whose concept has been introduced previously in [18] but not used in bioacoustics yet.

The organization of the paper is as follows. In section 2, an overview of the complex-valued autocorrelation function is given. A comparison to classical autocorrelation function is done to show the contribution of complex values in term of subharmonic suppression. We present how this initial algorithm can be extended by a time-period analysis to give a time-varying ICI spectrum and introduce a threshold function that can be applied on this spectrum to detect the different interleaved trains. In section 3, we validate the proposed algorithm on simulated and experimental data. Some conclusions are provided in section 4.

METHODOLOGY

Complex-Valued Autocorrelation Function

As stated, we rely only upon the TOA of each click as it is the only parameter that is totally independent of the relative orientation between the head of the whale and the hydrophone. For this reason, if t_n represents the TOA of each click ($n = 0, \dots, N - 1$) and N is the total number of clicks in the train, then the click train can be modeled as a sum of Diracs:

$$g(t) = \sum_{n=0}^{N-1} \delta(t - t_n) \quad (1)$$

where δ is the Dirac function and t_n the TOA of the n^{th} click.

The expression of the complex-valued autocorrelation function introduced in [16, 17] is given by:

$$D(\tau) = \int_{-\infty}^{+\infty} g(t)g(t - \tau) \exp(2\pi i t/\tau) dt \quad (2)$$

where τ is real and strictly positive.

As a comparison, we remind the expression of the classical autocorrelation function:

$$C(\tau) = \int_{-\infty}^{+\infty} g(t)g(t - \tau) dt \quad (3)$$

Combining equations (1) and (2) gives:

$$D(\tau) = \sum_{n=1}^{N-1} \sum_{m=0}^{n-1} \delta(\tau - (t_n - t_m)) \exp(2\pi i t_n/(t_n - t_m)) \quad (4)$$

Combining (1) and (3) gives:

$$C(\tau) = \sum_{n=1}^{N-1} \sum_{m=0}^{n-1} \delta(\tau - (t_n - t_m)) \quad (5)$$

Considering the particular case of a pulse train coming from a unique source, we can write:

$$t_n = (n + \eta)p \quad (6)$$

where $n = 1, \dots, N$; p is the ICI and η the initial phase. With such TOA expression, equation (4) becomes

$$D(\tau) = (N - 1)\delta(\tau - p) \exp(2\pi i \eta) + \sum_{l=2}^{N-1} \delta(\tau - lp) \frac{\sin(N\pi/l)}{\sin(\pi/l)} e^{\pi i(N+1+2\eta)/l} \quad (7)$$

The first term on the right hand side of equation (7) represents the contribution of impulses located at the fundamental ICI $\tau = p$ and its modulus is $N - 1$. The second term represents the contribution of impulses located at integer multiples of the ICI $\tau = lp$ and gives the amplitude of subharmonics. It is shown that this second term can be majored by $l/2$ and so, is independent from N [17]. Therefore when N increases subharmonics are suppressed in comparison to the amplitude of the peak corresponding to the fundamental ICI.

In the case of a single pulse train, the classical autocorrelation function gives the following result:

$$C(\tau) = \sum_{l=1}^{N-1} (N - l)\delta(\tau - lp) \quad (8)$$

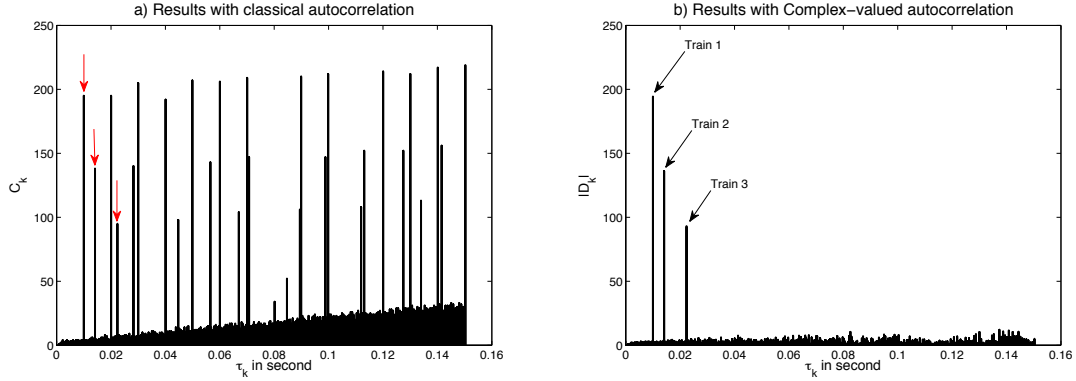


FIGURE 1: Comparison between the classical autocorrelation and the complex autocorrelation in the case of three interleaved click trains. (a) Results of the classical autocorrelation $C(\tau)$. (b) Results of the complex autocorrelation $|D(\tau)|$.

It is clear in equation (8) that for $l \geq 2$, $C(\tau)$ still depends on N . So, the higher is N , the more visible are the subharmonics.

An example is given on figure 1 to demonstrate the benefits of the complex-valued autocorrelation. Three simulated click trains, whose ICIs are 0.01 s, 0.014 s and 0.022 s, have been interleaved. On figure 1a, which shows the results of the classical autocorrelation, we can not know with certainty the number of interleaved trains and their respective ICIs. Peaks corresponding to the true ICIs (spotted by the arrows) are mixed up with the subharmonics. Figure 1b shows the results of the complex-valued autocorrelation function and clearly highlights the presence of the three interleaved click trains with peaks at τ -values equal to the the ICIs of each train.

Time-Rhythm Analysis

Principle

The limitation of the complex-valued autocorrelation function described in the previous subsection is that trains from each source must exist during most parts of the observation time to have a peak appearing in the spectrum. To overcome this problem a time-rhythm analysis methods is introduced in [18]. Time-rhythm analysis is is defined by:

$$D(t, \tau) = \int_{s \in W(t, \tau)} g(s)g(s + \tau) \exp(2\pi i s/\tau) ds \quad (9)$$

where $W(t, \tau) = [t - \nu\tau/2, t + \nu\tau/2]$ is a window sliding along the interleaved click trains. The window is centered around t and its width is $\nu\tau$ with ν a positive real number. As a result, we obtain an image called *time-varying ICI spectrum* on which the x-axis represents the time, the y-axis represents the ICI and the colormap represents the modulus of $|D(t, \tau)|$. Figure 2a shows such an image.

Train Detection

From this *time-varying ICI spectrum*, click trains can effectively be detected through thresholding. A pulse train exist if $|D(t, \tau_k)|$ exceeds this threshold. The threshold is calculated from noise statistics. A detailed description of the steps leading to the computation of this threshold is

made in [18]. We just remind the final expression:

$$Pfa = 1 - \Gamma \int_0^{\infty} \exp(\lambda(J_0(s) - 1)) J_1(\Gamma s) ds \quad (10)$$

where Pfa is the probability of False Alarm of the detector, Γ is the detection threshold, $J_0(\cdot)$ et $J_1(\cdot)$ are respectively the Bessel functions of order 0 and 1, and λ is given by:

$$\lambda = \frac{N_{\tau}^2(t)\sigma}{\nu} \quad (11)$$

with $N_{\tau}(t)$ the number of clicks in the moving window $W(t, \tau)$. Therefore, it is important to notice that with such expression for λ , the threshold adapts to the number of clicks in each window $W(t, \tau)$.

RESULTS

The method proposed in the previous section to de-interleave click trains has been tested on simulated and real data.

As odontocetes are able to change their ICI according to the time depending on their activity (localization, foraging), we have simulated five interleaved click trains with very different characteristics. Three of them are constant but lightly corrupted with some jitter to model a localization behavior and two others present accelerations and decelerations of the rhythm to model a foraging activity. These last two trains have their ICIs modulated with a cosine function to model the accelerations and decelerations. Table 1 presents in details the train characteristics.

TABLE 1: Characteristic of the five interleaved click trains

Train	Type	ICI	Jitter	Amplitude	Frequency	Time of beginning	Time of end
Train 1	constant	0.05 sec	10%			5 sec	8 sec
Train 2	constant	0.08 sec	10%			1 sec	8 sec
Train 3	constant	0.12 sec	10%			4 sec	7 sec
Train 4	modulated	0.02 sec	0 %	± 0.011 sec	0.1 Hz	2 sec	4 sec
Train 5	modulated	0.01 sec	0 %	± 0.005 sec	0.035 Hz	6 sec	10 sec

Figure 2 shows the results obtained with these five interleaved click trains. On figure 2a the result of the time-rhythm analysis, ie $|D(t, \tau_k)|$, has been plotted. Figure 2b shows the results after a thresholding. Both figures clearly show the five interleaved click trains. For the three constant trains, the ICIs found by the proposed method exactly correspond to those of the simulated trains. For the accelerating/decelerating trains we can clearly see changes in rhythm. At last, times of beginning and end found on these time-rhythm maps are nearly equal to the values given in table 1.

The proposed algorithm has also been validated on real data. Signals used for these validations are click trains of Bottlenose Dolphins (*Tursiops truncatus*), whose presence during the records at sea has been confirmed by visual observations. Click trains have been recorded in the English Channel between the Channel Islands and the French coast. Dolphins were in groups of 3 to 10 individuals. TOAs of the clicks have then been manually extracted through a visual inspection of the waveform. This list of extracted TOAs feeds our deinterleaving algorithm.

Results of the algorithm are plotted on figure 3. After the thresholding, 7 distinct segments corresponding to 7 detected click trains can clearly be distinguished. Some false alarms appear also between 250 and 251.5 seconds. Up to three interleaved click trains are simultaneously

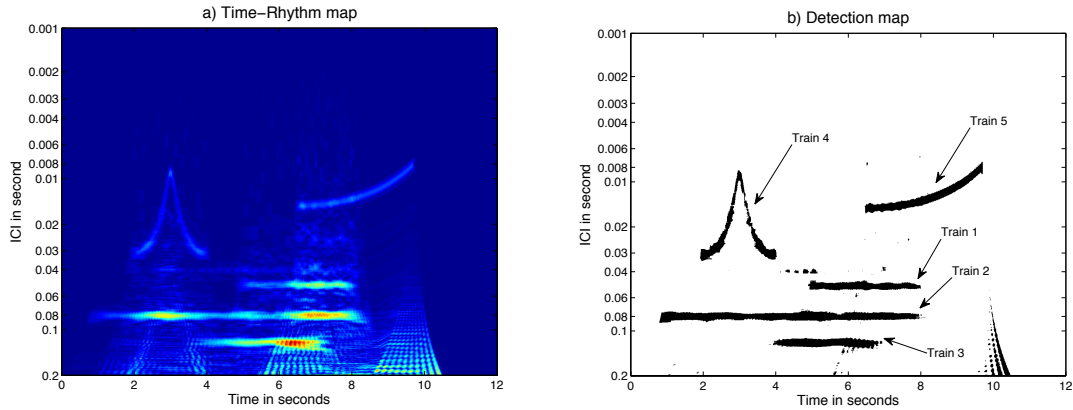


FIGURE 2: Results of the Time-Rhythm analysis on simulated data. (a) Time-varying ICI spectrum. x-axis represents the time and y-axis represents the ICI. (b) Time-varying ICI map after the thresholding step. x-axis represents the time and y-axis represents the ICI.

distinguished, which means that at least 3 dolphins were clicking simultaneously during this period. A visual inspection of the waveform and spectrogram reveals that 4 different dolphins were effectively clicking during this 10 seconds snapshot. As they are not always clicking continuously, some click trains are split in several segments.

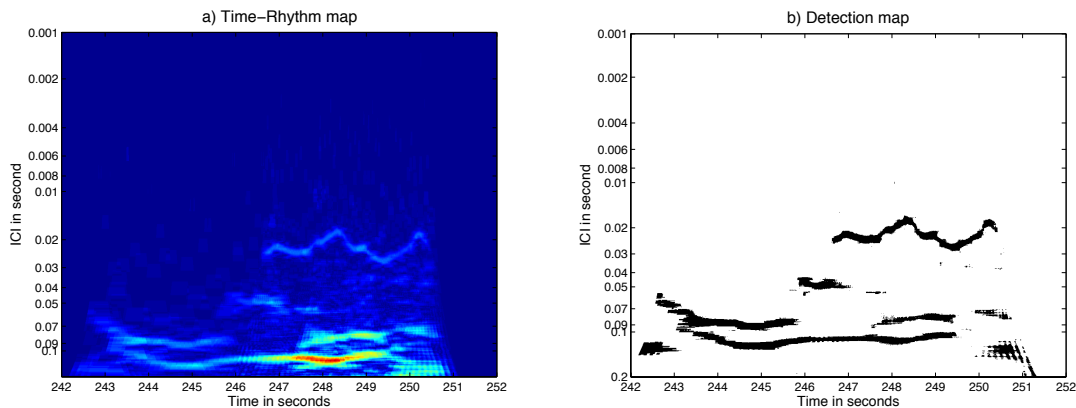


FIGURE 3: Results of the Time-Rhythm analysis on real data. (a) Time-varying ICI spectrum. x-axis represents the time and y-axis represents the ICI. (b) Time-varying ICI map after the thresholding step. x-axis represents the time and y-axis represents the ICI.

CONCLUSION

In this paper we have proposed a method to de-interleave click trains of odontocetes clicking simultaneously. We have also shown that the proposed time-rhythm representation allowed to track for changes in the rhythm. Based on a complex-valued autocorrelation function, the rhythm of each interleaved click train is highlighted, while the subharmonics corresponding integer multiples of the fundamental ICIs are suppressed. Therefore the number of individuals clicking simultaneously can be known. The proposed method has been validated on simulated and real data.

ACKNOWLEDGMENTS

Authors would like to thanks F. Gally from GECC (Cherbourg, France) and L. Di Iorio from Chaire Chorus, (Foundation Grenoble INP, Grenoble, France) for technical and material support during recordings at sea.

REFERENCES

- [1] W. M. X. Zimmer, M. P. Johnson, P. T. Madsen, and P. L. Tyack, “Echolocation clicks of free-ranging cuvier’s beaked whales (*ziphius cavirostris*)”, *Journal of Acoustical Society of America* **117**, 3919–3927 (2005).
- [2] R. Aubauer, M. O. Lammers, and W. L. Au, “One-hydrophone method of estimating distance and depth of phonating dolphins in shallow water”, *Journal of Acoustical Society of America* **107**, 2744–2749 (2000).
- [3] T. A. Marques, L. Thomas, J. Ward, J. DiMarzio, and P. L. Tyack, “Estimating cetacean population density using fixed passive acoustic sensors: An example with blainvilles beaked whales”, *Journal of Acoustical Society of America* **125**, 1982–1994 (2009).
- [4] W. W. L. Au, *The SONAR of Dolphins* (Springer) (1993).
- [5] C. Gervaise, Y. Simard, N. Roy, B. Kinda, and N. Menard, “Shipping noise in whale habitat: Characteristics, sources, budget, and impact on belugas in saguenay-st. lawrence marine park hub”, *Journal of Acoustical Society of America* **132**, 76–89 (2012).
- [6] D. Mellinger and K. Stafford, “An overview of fixed passive acoustic observation methods for cetaceans”, *Oceanography* **20**, 36 (2007).
- [7] P. Lepper, N. Dumortier, K. Dudzinski, and S. Datta, “Separation of complex excholocation signal trains from multiple bio-sonar sources”, in *Proceedings of the International Conference “Underwater Acoustic Measurements: Technologies & Results”* (2005).
- [8] P. Baggenstoss, “Separation of sperm whale click-trains for multipath rejection”, *Journal of Acoustical Society of America* **129**, 3598 (2011).
- [9] J. Starkhammar, J. Nilsson, M. Amundin, S. A. Kuczaj II, M. Almqvist, and H. W. Persson, “Separating overlapping click trains originating from multiple individuals in echolocation recordings”, *Journal of Acoustical Society of America* **129**, 458—466 (2011).
- [10] D. S. Houser, D. A. Helweg, and P. W. Moore, “Classification of dolphin echolocation clicks by energy and frequency distribution”, *Journal of Acoustical Society of America* **106**, 1579–1585 (1999).
- [11] R. Bahl, T. Ura, and T. Fukuchi, “Towards identification of sperm whales from their vocalizations”, *Seisan Kenkyu* **54**, 409–413 (2002).
- [12] W. X. Zimmer, “Passive acoustic monitoring of cetaceans”, Cambridge, University press] 52 – 53 (2011).
- [13] H. Mardia, “New techniques for the deinterleaving of repetitive sequences”, in *Radar and Signal Processing, IEE Proceedings*, volume 136, 149–154 (IET) (1989).

- [14] R. Wiley, “Electronic intelligence: The analysis of radar signals, pp”, Artech House **2nd edition**, chap 8 (1993).
- [15] D. Milojevic and B. Popovic, “Improved algorithm for the deinterleaving of radar pulses”, in *Radar and Signal Processing, IEE Proceedings*, volume 139, 98–104 (IET) (1992).
- [16] D. Nelson, “Special purpose correlation functions for improved signal detection and parameter estimation”, in *Acoustics, Speech, and Signal Processing, ICASSP, IEEE International Conference on*, volume 4, 73–76 (IEEE) (1993).
- [17] K. Nishiguchi and M. Kobayashi, “Improved algorithm for estimating pulse repetition intervals”, *Aerospace and Electronic Systems, IEEE Transactions on* **36**, 407–421 (2000).
- [18] K. Nishiguchi, “Time-period analysis for pulse train deinterleaving”, *Computers of the Society of Instrument and Control Engineers, Transaction on* **E-4**, 68–78 (2005).