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Rhythmic analysis for click train detection and source separation with examples on beluga whales

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ABSTRACT

Passive acoustic monitoring systems are used to study cetaceans through the sounds they produce. Among them, toothed whales emit sequences of acoustic impulses having a rhythmic pattern. As they generally live in pods, click trains from several individuals are often interleaved and recorded together with additional natural or anthropogenic impulsive sources. This paper presents an algorithm that uses the rhythmic properties of odontocete click trains for detecting rhythmic impulse trains embedded in other impulse sounds and de-interleaving click trains from simultaneous clicking odontocetes. The contributions of the article are: (1) a method to detect the presence/absence of rhythmic click trains and to characterize the time – Inter Click Interval (ICI) pattern of click trains; (2) an analytical analysis of the performances of this method (jitter, length of click trains); (3) the demonstration of its efficiency on real data with wild beluga whales recorded in Canada.

1. Introduction

Sounds produced by marine mammals can be separated in two broad categories: tonal-sounds and clicks. Clicks are very short impulses lasting only tens to hundreds of microseconds [1]. They are produced by all odontocetes (toothed whales) to locate and explore seafloor, submerged obstacles and preys or to communicate. Odontocetes generally emit sequences of several consecutive clicks called *click trains*. The Inter-Click Interval (ICI) ranges from a few microseconds to more than 2 s, and varies depending on the species and the activity of the individuals (echolocation, foraging, etc.) [1,2]. Trains with very short ICI ($\leqslant 20\ \mu s$) are called burst pulses [3]. ICI can vary during a train depending on the activity of the individual. As shown by previous studies, there is a random part and a deterministic part in these variations [4–7].

Tracking the deterministic component of the ICIs within click trains is of great interest to detect and separate rhythmic sources from a mixture of other impulsive sources like snapping shrimps, ice-cracking events or shipping cavitation impulses. This detection and separation task can quickly become difficult when the number of impulsive sources is very large.

Previous methods of detection and separation of odontocete click trains have been based on acoustic descriptors of clicks, such as the amplitude [5], the centroid and peak frequencies [8,9], the temporal properties [10,5], high order statistics of the waveform [6,11]. These methods use either only one or several of these descriptors and range from a simple correlation technics to advanced artificial neural network [12] or multi-hypothesis trackers [13,14]. Most of them need relatively invariable parameters and/or a-prior training. In a real context, these conditions are not suitable as odontocete clicks have narrow directional beam patterns [1,2,15,16] and most of their acoustic characteristics quickly change or even vanish with the animal orientation. To overcome this difficulty, the direction of arrival (DOA) of the clicks (i.e. the angular position of the sources) can be used as an alternative method to cluster clicks into trains [17,18]. However, this approach requires the use of an array of several hydrophones and the synchronized reception of each click from each source on all these hydrophones to compute the time difference of arrivals and deduce the DOA of each click. Additionally, individuals must be spatially distant to achieve a good separation of the clicks based on their DOAs.

Recently, Zaugg et al. [19] have proposed a method using a rhythmic analysis and a spectral dissimilarity measure to cluster

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interleaved sperm whale clicks into separate click trains. They introduced a metric to estimate the number of subsets of click trains per time unit and apply this metric in a data-mining context.

Unlike previous methods, in our paper we do not use the clicks acoustic descriptors or direction of arrivals but only their time of arrivals (TOA) and a rhythmic analysis algorithm to detect the presence of odontocete click trains. We assume that clicks coming from odontocetes have a rhythmic pattern whereas impulses from other sources have not. Compared to amplitude or spectral characteristics, which can vary greatly during the propagation of the acoustic wave in water, TOAs have the advantage of being less affected by these propagation conditions and by the directivity of the source. Furthermore, TOAs are easy and fast to estimate with traditional click detectors [20,21,11].

Classical TOA-based rhythmic algorithms use the autocorrelation of the click trains to build an histogram having peaks located at lags corresponding to ICI-values of the different interleaved trains [22–24]. It is known that autocorrelation also produces spurious peaks located at values corresponding to multiples of the fundamental ICIs. These subharmonics severely disturb the interpretation of the results. We propose to overcome this problem by using a complex autocorrelation function, which almost completely suppress subharmonics of the autocorrelation while keeping peaks located at the ICI-values of the interleaved trains [25,26]. Several improvements of this complex autocorrelation have been proposed [27–30] in a Radar community. Drawing on time–frequency representations Nishiguchi has introduced a time-rhythm (or time-ICI) representation, by computing the complex autocorrelation for windows sliding along the click train, leading to a time-ICI map.

Based on these previous works on the complex autocorrelation, we propose a method capitalizing on the rhythmic properties of odontocete click trains to: (1) detect click trains mixed with other impulsive sources; (2) separate interleaved click trains from several odontocetes emitting simultaneously. We transpose tools based on the complex autocorrelation function and the time-ICI detection to underwater bio-acoustics and passive acoustic monitoring (PAM) methodology. The key question is the behavior of these tools when they are faced with natural signals having their own specific variability rather than regular human-made RADAR signal. The first objective of our paper is to give a whole comprehensive description of this algorithm (from the raw data to the automatic segmentation/detection of time-ICI map). The second objective is to evaluate its analytical performances in regards to its different degrees of freedom. The final objective is to show its efficiency on real data of wild beluga.

To our knowledge, only Zaugg et al. [19] have used the complex autocorrelation for estimating the ICI of interleaved click trains. Our approach differs on several points. First, our algorithm does not perform preconditioning tests based on spectral dissimilarities between pairs of clicks to suppress some of them. Instead, we consider all click pairs as possible candidates for the rhythm analysis. So, our algorithm comes right after usual click detectors in the processing chain. Second, unlike Zaugg et al.'s algorithm, the analysis window is not centered on the detected clicks but slides along the click train as it is usually the case in time–frequency analysis. Third, the time-ICI representation obtained at the output of our algorithm has never been used in underwater bio-acoustics and offers several interesting applications.

In the first part of this paper, we present an overview of the complex autocorrelation function and its use with a sliding window to build a time-ICI representation. The second part deals with the performances of the algorithm from a theoretical and analytical point of view. The detectability of a click train depending on parameters such as the length of the train, the jitter and the presence of false alarms, is studied. In this part, we also study the ability of the algorithm to separate interleaved click trains. The third part, uses simulated examples to confirm results obtained in the performance analysis section. The last part shows the efficiency of the proposed method on real data from wild beluga whales recorded at sea.

2. Description of the algorithm

2.1. Overview

Prior to the proposed algorithm, clicks are detected on the waveform with standard click detectors [11,20,21] (top part of Fig. 1). Times of local maximum amplitude of the detected clicks are considered as the time of arrival (TOA) of the clicks. This latter list of TOAs is used to perform the rhythmic analysis and separate interleaved click trains. This processing is divided in three steps (Fig. 1).

The first step transforms the list of TOAs to a new representation called *time-ICI map* (Fig. 1). This transformation is based on the complex autocorrelation function, which highlights the fundamental ICIs of the interleaved click trains, while avoiding the subharmonics given by the classical autocorrelation. By calculating such complex-autocorrelation in sliding windows along the signal, we obtain a map with the time on the abscissa-axis, the ICI on the ordinate-axis and the amplitude of the autocorrelation on the elevation-axis.

The second step of the algorithm aims to calculate a threshold to identify peaks corresponding to click trains and suppress the possible noise or spurious spike on the time-ICI map. The third step is the thresholding of the time-ICI map to produce the binary time-ICI map more suitable to analyze and distinguish the rhythm of interleaved click-trains.

This method needs 7 input parameters to build the time-ICI representation and calculate the detection threshold (Table 1). Their values have an influence on the performance of the algorithm and are discussed in the performance analysis section. In the next subsections, we detail the signal processing techniques used in each of the three steps. We assume that the list of TOAs is already known so that our analyses do not depend on the click detector performances.

2.2. Complex autocorrelation vs classical autocorrelation

Nelson [25] and Nishiguchi [26] introduced the concept of complex-valued autocorrelation, which automatically suppresses subharmonics that normally appear when calculating the autocorrelation function of rhythmic click trains. The complex autocorrelation function is given by:

$$D(\tau) = \int_{-\infty}^{+\infty} m(t)m(t-\tau)\exp(2\pi i t/\tau)dt \qquad (1)$$

while the classical autocorrelation function is:

$$C(\tau) = \int_{-\infty}^{+\infty} m(t)m(t-\tau)dt \qquad (2)$$

where $\tau \in \mathbf{R}^{+}$ and $m(t)$ represents the click train. Considering that the TOA is the only parameter used to represent each click, this click train can be modeled as a sum of Dirac delta functions:

$$m(t) = \sum_{n=0}^{N-1} \delta(t - t_n) \qquad (3)$$

where t_n is the TOA of the nth click, $\delta(\cdot)$ is the Dirac delta function and N is the total number of clicks in the train.

As click detectors usually detect all kind of acoustic impulses, we assume that TOAs of $m(t)$ are a mixture of click trains emitted