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Odile Gérard, Craig Carthel, Stefano Coraluppi

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# Classification of Odontocete Buzz Clicks using a Multi-Hypothesis Tracker

Odile Gérard\*, Craig Carthel, and Stefano Coraluppi

NATO Undersea Research Centre, Viale S. Bartolomeo 400, 19126 La Spezia, Italy

\* Contact author. E-mail: [odileg@free.fr](mailto:odileg@free.fr)

**Abstract**—Blainville’s beaked whale (*Mesoplodon densirostris*) buzz clicks have been found to have characteristics that can vary significantly. While we have not succeeded to classify them individually, we find that their spectrum is very similar from one click to the next. In previous work, we showed that a multi-hypothesis tracker can be used to associate these clicks, and subsequently to classify the click sequence. This paper describes further tracker enhancements and shows improved performance results. Further, we find that the property of slowly varying buzz clicks spectrum is also true for other odontocete species, and apply our multi-hypothesis tracking algorithm to such data.

**Index terms**—Target tracking, data association, classification, odontocete buzzes

## I. INTRODUCTION

Toothed whales are known to click to find prey. The characteristics of the clicks and repetition rates vary from one species to another, but clicks are fairly regular during the phase in which the animals are looking for prey. Once they have found prey the repetition rate of the clicks increases; these sequences are called buzzes. Previous work has been done to detect and classify Blainville’s beaked whale (*Mesoplodon densirostris*) clicks automatically, and subsequently to determine how many animals are present [1]. A transient detector using the Page test [2] has been developed to extract clicks which are characterized by click time, click duration, click amplitude and spectral information. A probability distribution over species is assigned to each click, based on its spectral information. The estimation of the number of animals is performed using a feature-aided multi-hypothesis tracking (MHT) algorithm to associate clicks that originate from the same animal. The association is based on the assumptions of slowly-varying click amplitude, Inter-Click Interval (ICI) and utilizes species classification information.

The Blainville’s beaked whale buzz clicks are known to differ from the regular ones [3]. Some of them have the characteristics described in [3], but others have characteristics that can significantly differ [4]. While we did not succeed to classify these clicks individually because of the variation of their characteristics, we found that their spectrum is very similar from one click to the next [4]. Thus, the multi-hypothesis tracking algorithm was modified to use this property of slowly varying spectrum of buzz clicks to permit their association as a sequence [5]. Under this scheme, buzz classification follows automatic tracking of click sequences.

It is common to have some missing click detections in a buzz, leading to track fragmentation. In this work, we enhance the processing scheme in [5] by allowing for missed detections, thus reducing the fragmentation of buzz tracks. The property of slowly varying spectrum of buzz clicks appears to be true for other species; thus, we apply our multi-hypothesis tracking algorithm to such data to validate the feasibility of click association followed by buzz classification in more general settings.

Section 2 provides some background on multi-hypothesis tracking (MHT), while section 3 describes the specific instantiation of the MHT functionality to click association. Section 4 provides a comparison of previously obtained results [5] with the results we obtain with our enhanced tracker for a Blainville’s beaked whale dataset. Section 5 provides results for some other species. Conclusion and future work are given in section 6.

## II. MULTI-HYPOTHESIS TRACKING

The multi-hypothesis tracker that forms the basis for the click tracker utilized in this paper is described in [6]; the algorithm was originally designed for active-sonar tracking, but its flexibility allows for appropriate modification to the click-association problem.

We illustrate the basic track-oriented *multi-hypothesis tracking* (MHT) approach with a simple example, shown in figure 1.

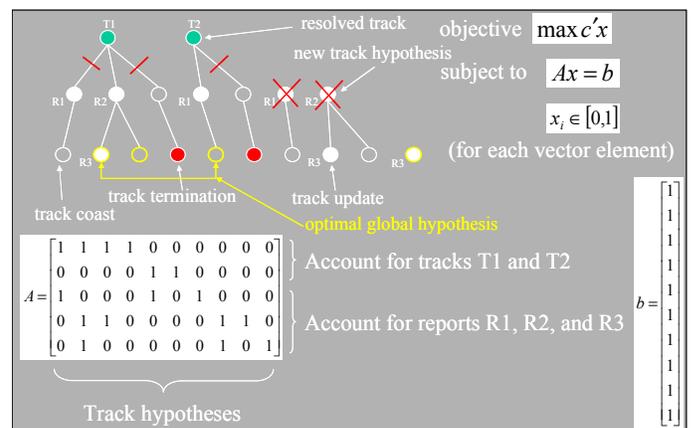


Figure 1: A simple MHT example.

The example assumes that two tracks, T1 and T2, have already been *resolved*. That is, prior data association decisions have led to a single global hypothesis that includes two tracks. Next, assume that a scan of data is received with two measurements, R1 and R2. Assume further that both R1 and R2 can feasibly be associated with T1, while only R1 can feasibly be associated with T2. This leads to a number of *local* (or *track*) hypotheses. Note that this set of hypotheses includes track continuation in the absence of a measurement (often denoted a track *coast*), as well as new-track hypotheses. A second scan of data includes a single measurement R3. We assume that R3 provides feasible updates to track hypotheses that include R2, as well as spawning a new-track hypothesis. Note that we assume that tracks are terminated after two coasts, indicated by the red icons in figure 1.

While the example includes a number of track hypotheses, it is important to note that each *global* hypothesis provide a complete set of data-association decisions that account for all resolved tracks and all sensor measurements. The number of global hypotheses is large, even for this simple example; the power of the track-oriented approach is that we do not require an explicit enumeration of global hypotheses.

Each track hypothesis has an associated log-likelihood score that reflects track initiation and termination penalties as well as nonlinear filtering scoring; in the case of linear Gaussian systems, this scoring is based on the filter *innovations*. The vector  $c$  includes the track-hypothesis scores. We are interested in the optimal global hypothesis, which amounts to identifying a vector  $x$  such that the global log-likelihood is maximized: the *maximum likelihood* solution. Having identified this solution through a two-stage relaxation approach based on linear programming or Lagrangian relaxation (solution is noted in yellow in figure 1), many *conflicting* local hypotheses are removed. In particular, those track hypotheses that differ in the first scan past the resolved hypothesis layer are removed, while those that differ in the more recent past are maintained.

Having pruned the set of track hypothesis trees (with 5 surviving track hypotheses), we are ready for a new scan of data. In the example, the resolved layer always lags the current time by one scan: thus we have a multi-hypothesis example with hypothesis-tree depth (*n-scan*) of one.

### III. THE CLICK TRACKER

The filtering and data association methodology used in [6] and described in section 2 can be used in a novel manner to support the analysis of click data. The objective is to associate click sequences, including buzz sequences, with the objective of determining the number of vocalizing mammals, as well as to classify these by species.

The formulation above requires the concept of a slowly-varying target *state*; here, the state is given by the inter-click interval (ICI) and click amplitude. Previously, we had also included species type as a (static) state component [1], though

subsequent analysis with a wider range of datasets revealed the difficulty in single-click classification. Instead, we introduced the click spectrum as a state component [5].

For simplicity, in [5] we assumed no measurement noise in the recursive filtering process. Thus, each association of a click to a click track results in a state update that replaces the previous state with the current state measurement. We have maintained this simplification here.

Secondly, again for simplicity, the tracker as described in [5] used an assumption in the state prediction stage, whereby the predicted state uncertainty did not depend fully on the prediction time step; this simplification has been removed here, so that the ICI uncertainty reflects the prediction time step.

The third simplification of note in [5] was the assumption that no missed clicks were present in the dataset. We have relaxed this assumption [5], allowing for a (user-defined) number of missed clicks before track termination. As we will see, this enhancement leads to a considerable reduction in track confirmation.

Not all associated click sequences lead to confirmed tracks. In particular, the tracker employs both an *M-of-N* track initiation filter, as well as a *track-length* filter, allowing for spurious association sequences to be removed as part of the tracking process. The result is a relatively small number of confirmed tracks, with few false click sequences.

As will be illustrated in the sequel, the enhanced tracker exhibits reduced fragmentation as well as a reduction in incorrect ICI estimates that are multiples of the true ICI.

In the track displays to follow, a new color is used each time a new track is plotted, with five colors used in total. For a given track, we use the same color in both the amplitude and ICI track displays.

## IV. RESULTS ON BLAINVILLE'S BEAKED WHALE BUZZES

### A. Description of the dataset and buzz click characteristics

Two datasets are considered, both of which can be obtained from the MobySound website [7]. The first dataset was recorded at the Atlantic Undersea Test and Evaluation Center (AUTEK) located off Andros Island, Bahamas, and was provided by the organizers of the 3rd International Workshop on the Detection and Classification of Marine Mammals using Passive Acoustics, Boston, July 2007 [8]. The second dataset was recorded by a DTAG [9] floating at depth in El Hierro, Canary Islands, Spain, and has been made available by Mark Johnson.

As described in [8], the dataset recorded at AUTEK in the Bahamas consists of training and test data; the training data includes sixteen cuts of Blainville's beaked whale from 0.5 to 3 minutes in length, the test data includes one cut of 10 minutes for which only Blainville's beaked whales are present. The sampling frequency is 96 kHz. Nine buzzes were found in five of the training files and eight other buzzes

were found in the test file. The duration of the buzzes of this dataset vary from 200 ms to 6 s.

The dataset recorded by the DTAG in the Canary Islands *consists of* 21 minutes of data sampled at 192 kHz. The quality of the data decreases with time, most likely due to the increase in the distance between the whales and the DTAG. Three short buzzes have been detected.

The Blainville's beaked whale produces two distinct click types: one during the search and approach phase (called regular clicks) and the second during the capture phase (called buzz clicks) [3, 10]. The first ones have most of their energy concentrated between 26 to 51 kHz and last around 270  $\mu$ s. The second ones have most of their energy concentrated between 25 to 80 kHz and last around 100  $\mu$ s [3]. In the Blainville's beaked whale dataset recorded by the DTAG in the Canary Islands, the buzz clicks have the characteristics described above. In the Blainville's beaked whale dataset recorded at AUTEK in the Bahamas, the buzz clicks vary and can differ significantly from the characteristics described above.

Fig. 2 gives the spectrogram of one long buzz recorded at AUTEK in the Bahamas. The visualization of the buzz appears blurred towards the end: this phenomenon is due to the relatively large time discretization employed, which is required for the visualization of the full buzz in a single image. In this figure we can see how much the characteristics (in particular the peak frequency) of a click of the same buzz can vary. The duration of the buzz click have been found to vary from 100  $\mu$ s to 800  $\mu$ s and the peak frequency from 17 to 35 kHz [4].

We did not find a means for single-click classification because even in the same buzz the characteristics of the clicks vary noticeably. However, we observed that from one click to the next the peak frequency and the shape of the spectrum are very close. Fig. 3 gives the spectrum of the first ten clicks (with the peak frequency less than 20 kHz) as well as ten near the end (with a peak frequency above 25 kHz) of the buzz illustrated in Fig. 2. We see that the spectrum of the clicks that are close in time are similar, and during the buzz the shape of the spectrum is slowly varying from the initial shape to the final one. The slow variation of the spectrum clicks in a buzz is true for all the buzzes present in these datasets.

### B. Previously obtained results

The multi-hypothesis tracking algorithm in [1] was modified to use the property of slowly varying spectrum of buzz clicks to permit their association as a sequence [5]. Under this scheme, buzz classification follows the automatic tracking of clicks. To achieve a good detection on the buzzes, the transient detector threshold is low. Correspondingly, all buzzes in the datasets were detected.

Fig. 4 gives the transient detector output sequence (in red) and the amplitude of the tracks obtained with the MHT tracker on a short buzz of the Canary Islands dataset. Fig. 5 gives the ICI of the tracks corresponding to Fig. 4. In this example we

can see the existence of a track with a false ICI (magenta track) at the beginning of the buzz due to miss detected clicks a track is formed on not consecutive clicks.

Fig. 6 gives the transient detector output sequence (in red) and the amplitude of the tracks obtained with the MHT tracker on a long buzz of the test file recorded in the Bahamas. Fig. 7 gives the ICI of the tracks corresponding to Fig. 6. In this example the buzz detection is fragmented in six tracks.

Fig. 8 gives the transient detector output sequence (in red) and the amplitude of the tracks obtained with the MHT tracker on another long buzz of the test file recorded in the Bahamas. Fig. 9 gives the ICI of the tracks corresponding to Fig. 8. In this example the buzz detection is fragmented in five tracks.

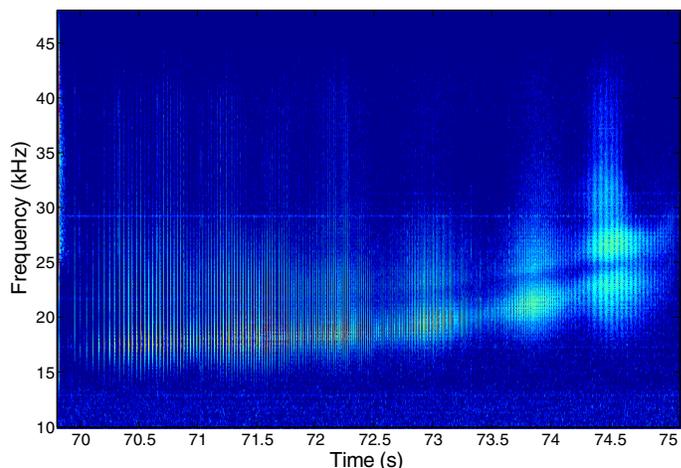


Figure 2: Spectrogram of a long buzz recorded at AUTEK in the Bahamas

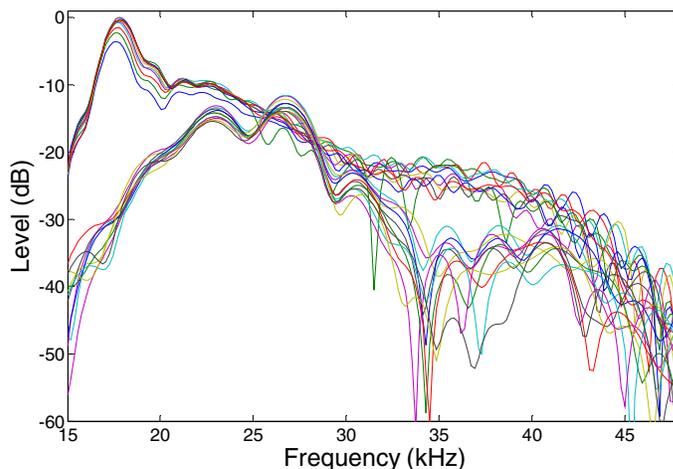


Figure 3: Spectrum of the first ten clicks and ten clicks near the end of the buzz illustrated in Fig. 2

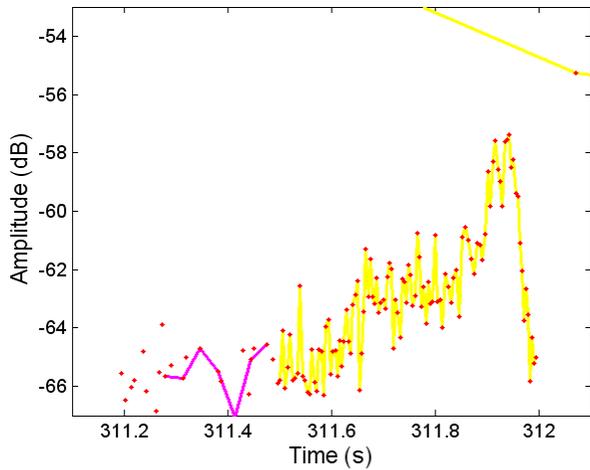


Figure 4: Click amplitude sequence (red) and MHT output (other colors) for a buzz of the Canary Islands dataset.

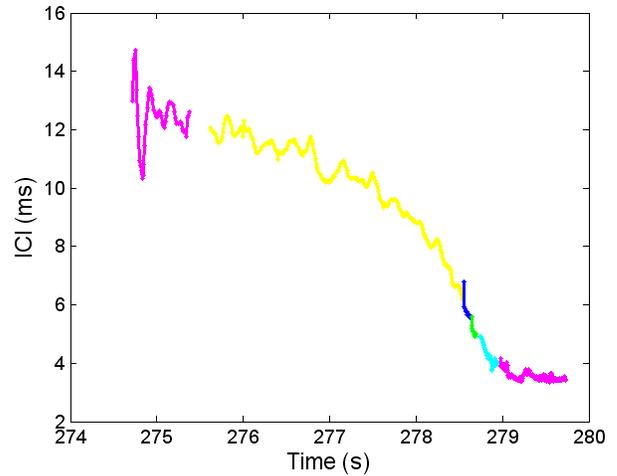


Figure 7: Sequences of ICIs for tracks generated by the MHT tracker, on the buzz corresponding to Fig. 6.

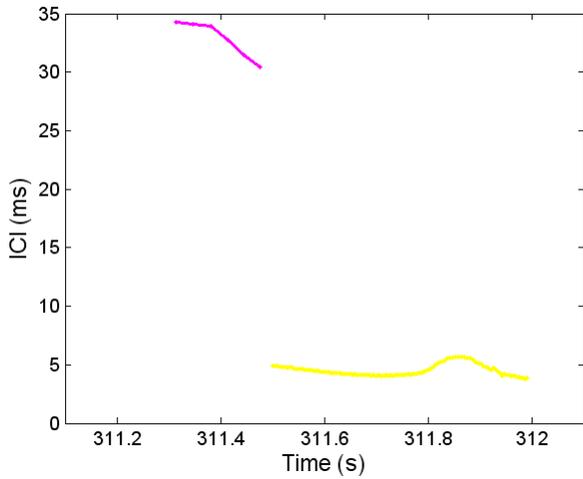


Figure 5: Sequences of ICIs for tracks generated by the MHT tracker, on the buzz corresponding to Fig. 4.

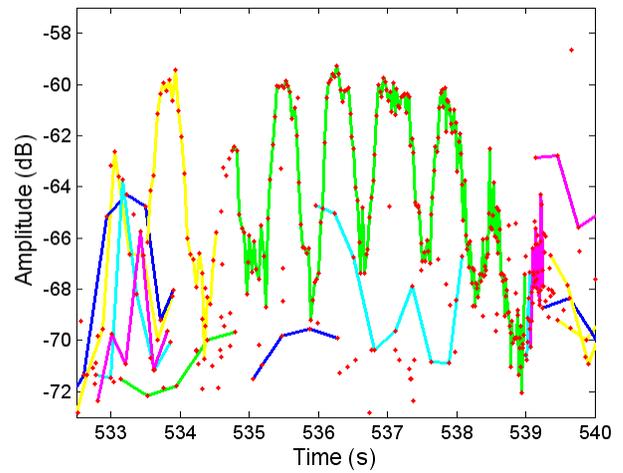


Figure 8: Click amplitude sequence (red) and MHT output (other colors) for another long buzz of the test file recorded in the Bahamas.

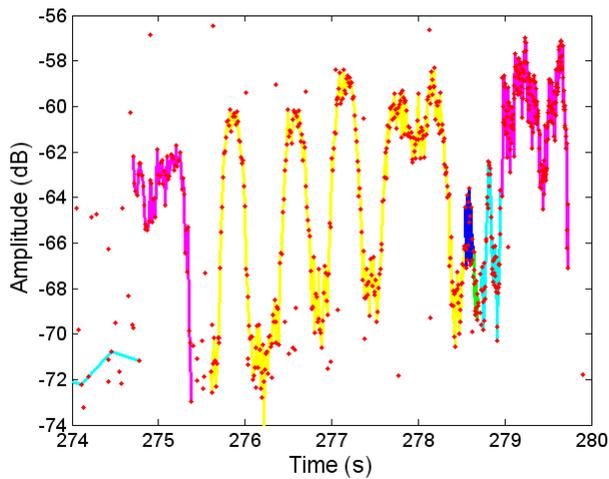


Figure 6: Click amplitude sequence (red) and MHT output (other colors) for a long buzz of the test file recorded in the Bahamas.

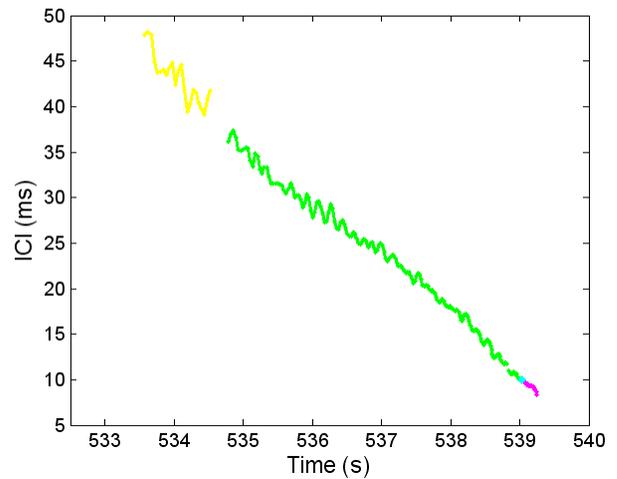


Figure 9: Sequences of ICIs for tracks generated by the MHT tracker, on the buzz corresponding to Fig. 8.

*C. Results obtained with the enhanced version of the click tracker*

In this paragraph we give the results obtained with the enhanced click tracker, for the same buzz as in the previous paragraph.

In figures 10-15, the number of missed detection allowed is 2, and the *M-of-N* setting for track initiation is 9-of-100 instead of 6-of-100 as in the previous paragraph. It seems logical to use a more stringent *M-of-N* setting when we increase the number of allowed missed detection. All the other parameters remain the same than in the previous paragraph.

Fig. 10 and Fig. 11 give the results of the modified tracker corresponding to the same buzz as in Fig. 4 and Fig. 5. There are still two tracks formed on this buzz, but both tracks now have the correct ICI.

Fig. 12 and Fig. 13 give the results of the modified tracker corresponding to the same buzz as in Fig. 6 and Fig. 7. The track of this buzz is fragmented in three pieces instead of six as in the previous version. There is less fragmentation (two) for a number of allowed missed detection of six.

Fig. 14 and Fig. 15 give the results of the enhanced tracker corresponding to the same buzz as in Fig. 8 and Fig. 9. The buzz track is fragmented in four pieces instead of five in the previous version.

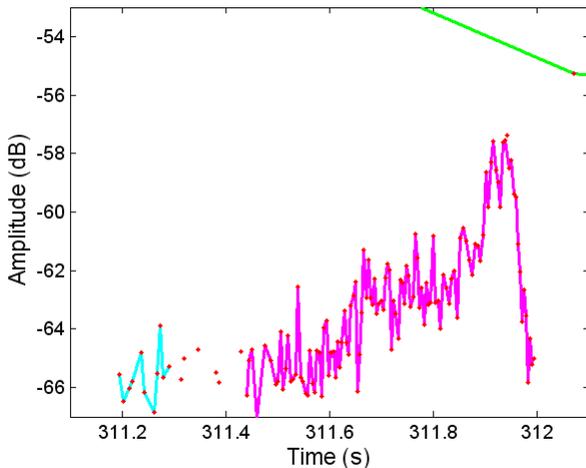


Figure 10: Click amplitude sequence (red) and new MHT output (other colors) for the buzz of the Canary Islands dataset corresponding to Fig. 4.

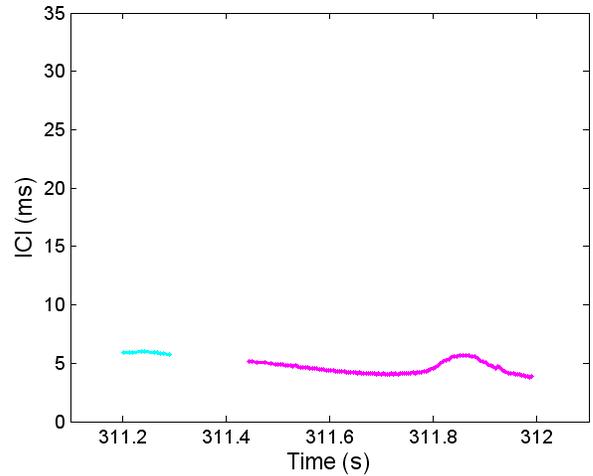


Figure 11: Sequences of ICIs for tracks generated by the new MHT tracker, on the buzz corresponding to Fig. 10 (to compare to Fig 5).

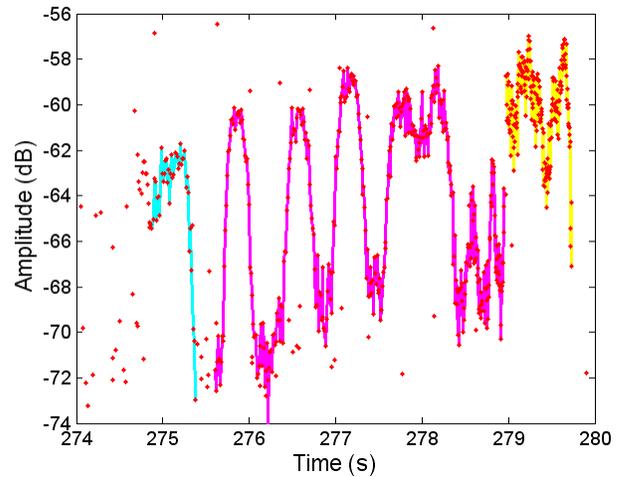


Figure 12: Click amplitude sequence (red) and new MHT output (other colors) for the long buzz of the test file recorded in the Bahamas corresponding to Fig. 6.

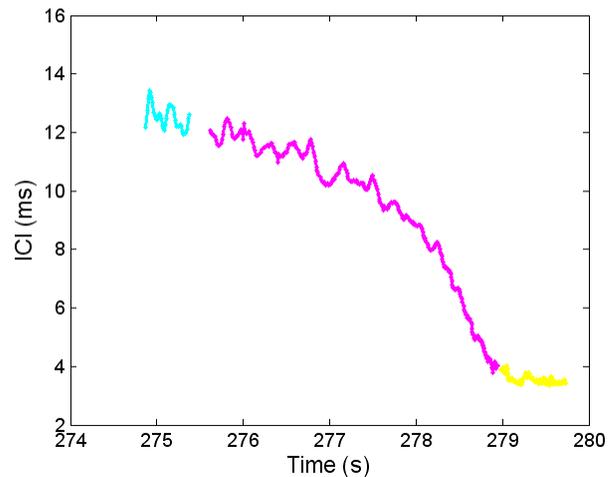


Figure 13: Sequences of ICIs for tracks generated by the new MHT tracker, on the buzz corresponding to Fig. 12 (to compare to Fig.7).

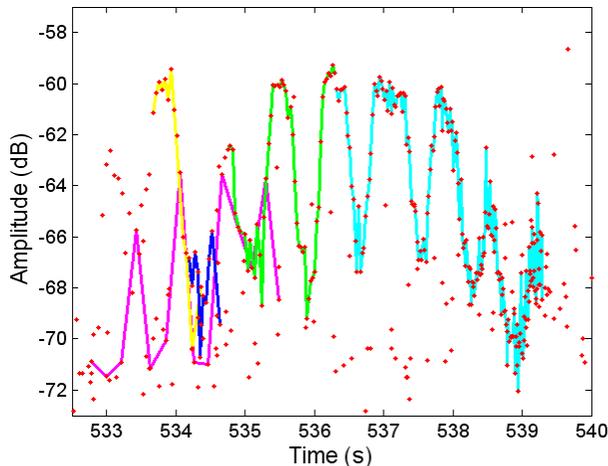


Figure 14: Click amplitude sequence (red) and new MHT output (other colors) for the long buzz of the test file recorded in the Bahamas corresponding to Fig. 8.

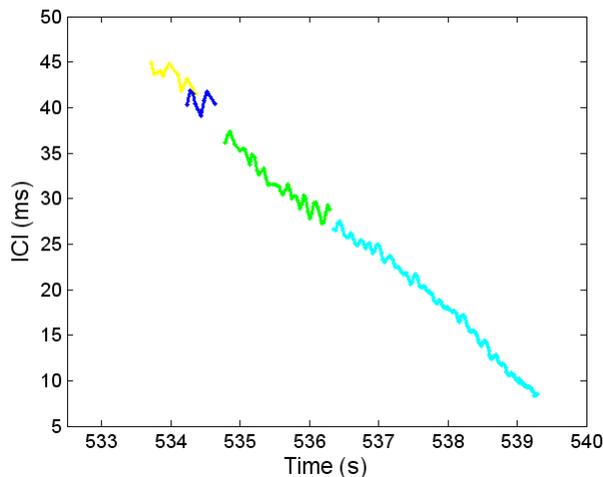


Figure 15: Sequences of ICIs for tracks generated by the new MHT tracker, on the buzz corresponding to Fig. 14 (to compare to Fig. 9).

#### D. Conclusion

The enhanced click tracker always gave equal or better results for all buzzes of the dataset relative to the results reported in [5], though less clear improvement is achieved in the example in Fig. 14 and Fig. 15. The most critical parameter appears to be the number of allowed missed detections; further, the choice of  $M$  (number of contacts) in the initiation sliding window of size  $N$ , is critical in reducing the number of false tracks.

## V. RESULTS ON OTHER ODONTOCETES BUZZES

The property of slowly varying spectrum of buzz clicks seems to be true for other species; correspondingly, we have applied our multi-hypothesis tracking algorithm on buzzes of sperm whales (*Physeter macrocephalus*), striped dolphins (*Stenella coeruleoalba*), Risso's dolphin (*Grampus griseus*), and also on some buzzes recorded in Mediterranean Sea but

for which the species has not been identified. We have consistently found satisfactory results. To optimize the results, it is likely that the detector and tracker parameters should be adjusted for each species. An example is given in Fig. 16 for sperm whales, which seems to be the species for which the method is the most challenged. There are several reasons that may explain the difficulties encountered for the sperm whale: sperm whale clicks are very different from those of other species, and the transient detector is not optimized for these clicks. An error in the detection of the click gives an error in the click time as well as the click spectrum. Additionally, the sperm whale ICI is a lot higher than for other species, and decreases more smoothly to the buzz ICI, requiring an effective handling of the transition phase.

#### A. Description of the dataset

The dataset used for this example was recorded at the Atlantic Undersea Test and Evaluation Center (AUTC) located off Andros Island, Bahamas, and is one of the test files provided by the organizers of the 3rd International Workshop on the Detection and Classification of Marine Mammals using Passive Acoustics, Boston, July 2007 [8]. It can also be obtained from the Mobysound website [7].

Many whales seem to be present in this dataset; we infer this due to the number of clicks detected per second and the typical ICI of sperm whale, which is closed to 1 second. Four buzzes are present in this dataset.

#### B. Results

Because of the differences in sperm whale buzz clicks, the parameters have been set differently: less stringent association test for the ICI variation, and more stringent association test for the amplitude variation.

Fig. 16 gives the sequence of tracker-generated ICIs for this dataset. We can see that all four buzzes have been detected. For two of them, the tracks are fragmented and not complete, while for the two others the tracks are not fragmented and almost complete. For the first buzz, many clicks are not detected; this explains why it is not possible to achieve a unique track on this buzz.

#### C. Conclusion

Although the sperm whale buzzes are challenging for this method, all buzzes are detected, and with the right ICI. It is of interest to study if these results can be improved by optimizing the selection of algorithmic parameters for this species.

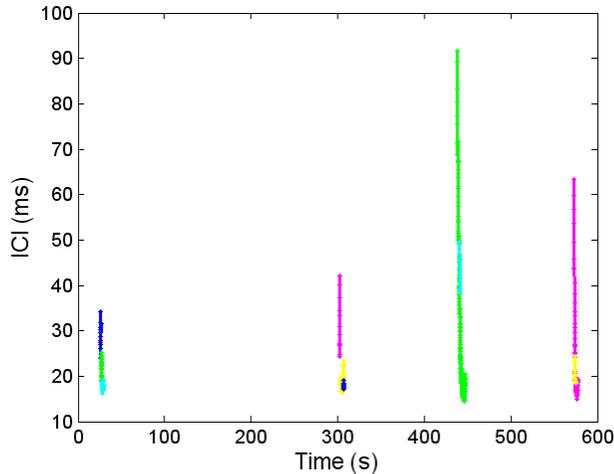


Figure 16: Sequences of ICIs for tracks generated by the new MHT tracker, on the sperm whale dataset.

## VI. CONCLUSIONS

In this paper, we have described an improved MHT approach to click association, allowing for an improved estimate of the number of click sequences. We have focused on analysis of the method on buzz clicks. The modification in filter uncertainty predictions for ICIs, as well as allowing missed detections in click sequences, improves our previously reported tracker results [5] on Blainville's beaked whale buzz classification. Additionally, we have investigated the application of our click tracker for the detection and classification of many other odontocete buzzes from other species.

It is important to note that the detection and classification of buzz clicks with our method requires that most clicks be detected; in turn, this requires a low threshold on the transient detector. This can be computationally challenging in datasets with numerous animals that have low ICIs (e.g. dolphins).

Finally, the correct determination of click spectrum requires an accurate determination of click time and duration. This requires that the dataset have high SNR in the frequency band in which the clicks are detected. An interesting step forward would be to build a click simulator in order to optimize the choice of detector and tracker parameters, as well as to provide a statistical characterization of algorithmic performance.

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# Document Data Sheet

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