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DETECTION OF SEA TURTLES USING ACTIVE SONAR

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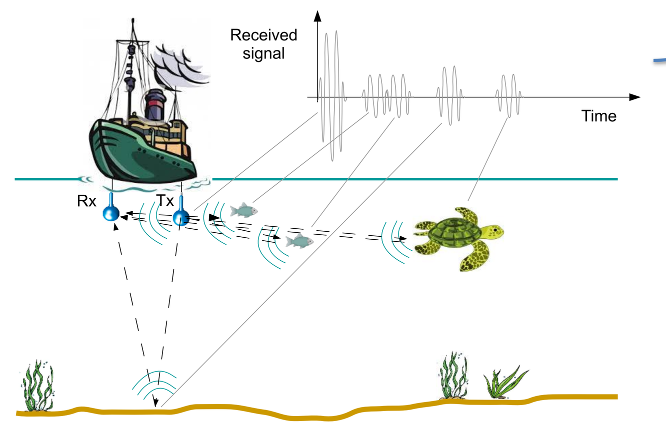
We offer a novel active sonar detector for sea turtles, that is able to reduce the false alarm rate through clustering. Our method mostly applies to the case where the signal-to-noise ratio of the acoustic reflections is fast time-varying and detections are sporadic. We start by accumulating a sequence of reflection patterns from the active sonar in a reflection matrix. Then, geometrical relations between the matrix's entries are recognized based on expected motion and size of the turtles, and blobs of potential targets are identified. Finally, identified targets are validated by their spatial features, namely, the blob's spatial size, and the strength of the inner connectivity between the cluster's members. Results of emulations, where we combined simulated targets with real measured reflections from clutter, demonstrate a good trade-off between the false alarm rate and the detection probability that far exceeds that of filtering-based benchmarks. Future work will involve testing our method on experimental data containing acoustic reflections from sea turtles.

Introduction

- Sea turtles has important contribution to the health of coastal and marine ecosystems, by maintenance of coral reefs, sea grass meadows, etc.
- Sea-turtle population monitoring is mostly done on nesting-beaches, by counting nests or individual female nesters.
- While additional independent monitoring methods can be of great value fo r ecologists, they are hard to apply since sea turtles are migrating species, that spend most of the time off-shore. Thus, a monitoring method that can detect swimming and submerged sea turtles is an advantage.
- Active acoustic detection involves transmitting an acoustic ping, detecting the reflected echoes, and identifying the echoes that reflect from a target of interest.
- Active acoustic detection has the potential to remotely detect swimming sea turtles.
- The main challenge in using low-frequency active sonar (LFAS) in shallow water is the low signal-to-clutter ratio (SCR), that is often encountered.
- Depending on the detection threshold, this results with either many false a larms [1], or a challenge to detect the presence of a target.
- Methods to deal with false alarms include classification of echoes by their backscatter intensity [1], and deep neural networks to classify the matche d filter's output [2], or its spectrogram [3].
- Dealing with a challenge to detect can combine tracking to apply track-before-detect (TkBD) approaches [4] [5].
- Our method focuses on the case in which the signal-to-noise ratio of the a coustic reflections is fast time-varying and detections are sporadic.
- Our input is a waterfall image after matched filter (MF) detection. We look for potentially connected data points that are detected by the MF, and cluster them into 'blobs'. Once clusters are formed, we classify them by their connectivity to be either target or clutter.
- The false alarm rate (FAR) is reduced since we require multiple detections to form a blob and to classify it, thus making our method more robust to false-alarms (FA) than classification based approaches that relay on a single data point at a time.

System model

- An omnidirectional transmitter and an omnidirectional receiver, located close to each other on the same platform.
- A bound on the maximal velocity of the target, but no other assumptions on the target's path.
- Target is moving slowly → no Doppler is considered.
- Reflections from target are weak → no multipath is considered.
- Matched filter (MF) applied on the received acoustic signal, outputs of MF at each ping are stacked to get a waterfall image.

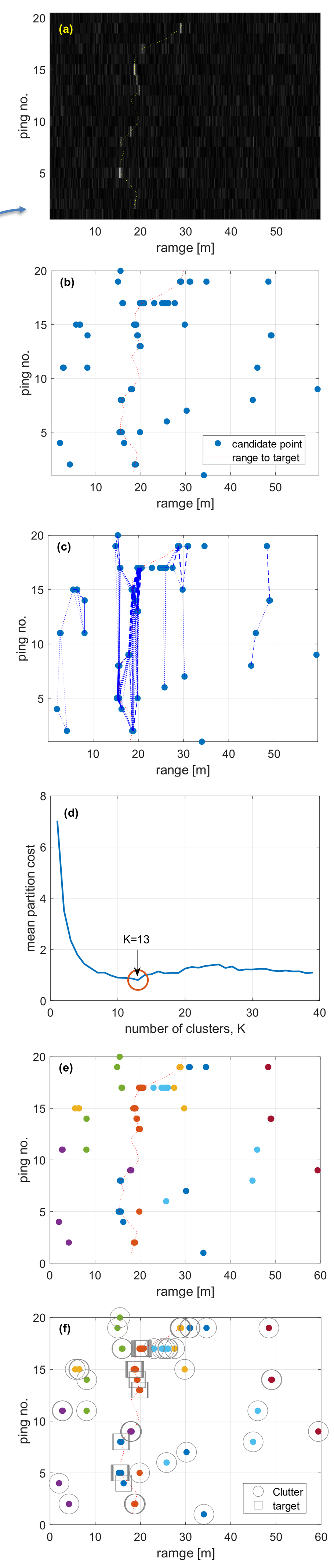


Methodology

Waterfall image → Identify candidate data points → Quantify connectivity → Clustering → Classify clusters → Decision: Target/clutter

Due to the low SCR, we expect this stage to detect also clutter

Cluster the candidate data points to identify potential blobs.



(a) Waterfall image: we expect target indications to appear as occasional blobs along the target's path.

(b) Preliminary detection --> N candidate data points.

$|r_i - r_j|$ $\quad$ $|t_i - t_j|$

distance between data points $\quad \Delta_{ij} = \beta\frac{\Delta r_{ij}}{\sigma} + \frac{\Delta t_{ij}}{\tau}$ $\quad$ target's size

(c) Encode connections into a weighted graph.

weighted adjacency matrix, $\mathbf{W}$ $\quad w_{ij} = \frac{1}{1+e^{-(v_{max}\Delta t_{ij}-\Delta r_{ij})}}e^{-\Delta_{ij}}$

$d_i = \sum_{j=1}^{N} w_{ij}$ $\qquad a_{ij} = \begin{cases} w_{ij}, & i \neq j \\ 0, & i = j \end{cases}$

graph-Laplacian $\quad \mathbf{L} = \mathbf{D}^{-1/2}(\mathbf{D}-\mathbf{A})\mathbf{D}^{-1/2}$

(d) Identify clusters by spectral clustering [6]. Choose number of clusters by minimal partition cost:

$$\underset{K}{\text{argmin}} \ \frac{1}{K}\sum_{k=1}^{K}\mathbf{b}_k^{\mathrm{T}}\mathbf{L}\mathbf{b}_k$$

K clusters, $b_i \in [0,1]$

subject to: $\mathbf{b}_k^{\mathrm{T}}\mathbf{b}_\mathbf{l} = 0 \forall k \neq l$

(e) Assign K clusters (clusters are color-coded)

$$(\mathbf{b}_k)_i = 1 \Rightarrow i \in \text{cluster k}$$

(f) Classify by cluster 'stability'

threshold

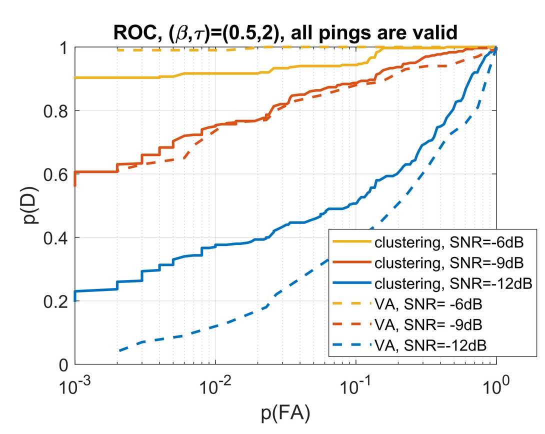
$$class(i) = \begin{cases} 0, & \mathbf{b}_k^{\mathrm{T}}\mathbf{W}\mathbf{b}_k < \eta & \text{(clutter)} \\ 1, & \mathbf{b}_k^{\mathrm{T}}\mathbf{W}\mathbf{b}_k \geq \eta & \text{(target)} \end{cases}$$

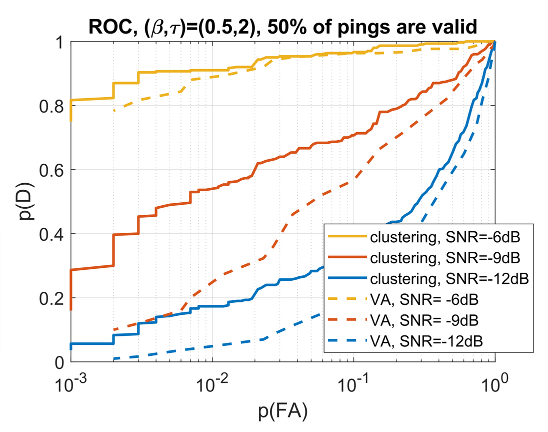
Simulation setup

- Each simulation scenario is a waterfall image: 20 pings × 60m.
- Target's path is randomly generated.
- Transmission signal: 10ms linear frequency modulated (LFM) chirp, 7-17kHz
- An echo from a target is simulated as a frequency-colored template of the transmitted signal.
- Clutter is emulated by randomly picking sections from recordings that contain echoes from clutter.
- We synthesize a time-domain signal for each ping, by replacing the samples of the clutter signal at the time corresponding to the echo from the target.
- MF is applied on the synthesized signal.
- Stack outputs of MF to get a waterfall image for a full simulation scenario.

Preliminary results

- Detection is measured per 20-pings waterfall scenario.
- We compared our method to a benchmark that uses the Viterbi-algorithm (VA) to perform track-before detect (TkBD) [7].





- When all pings are reflected (left figure), our performance are similar to the VA-based TkBD for SNR = -9dB, and better for lower SNR.
- This effect is increased when reflection from some pings is not detected, i.e., 'blob' effect (right figure): while both methods are affected, our method is more robust.

References

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CONCLUSION AND FUTURE WORK

Conclusions

- We propose a detection method for active sonar that is designed to cope with real-world challenges, which limit the performance of current state-of-the-art methods.
- We tested our method on a realistic simulation framework, and illustrated its superiority over VA-based TkBD.

Future work

- Improve classification: test spectral features that characterize acoustic reflections from sea-turtles and distinguish them from clutter.
- Test our method on experimental data containing acoustic reflections from sea-turtles.