

Multi-target tracking using Probability Hypothesis Density (PHD) filters for whistle contour detection

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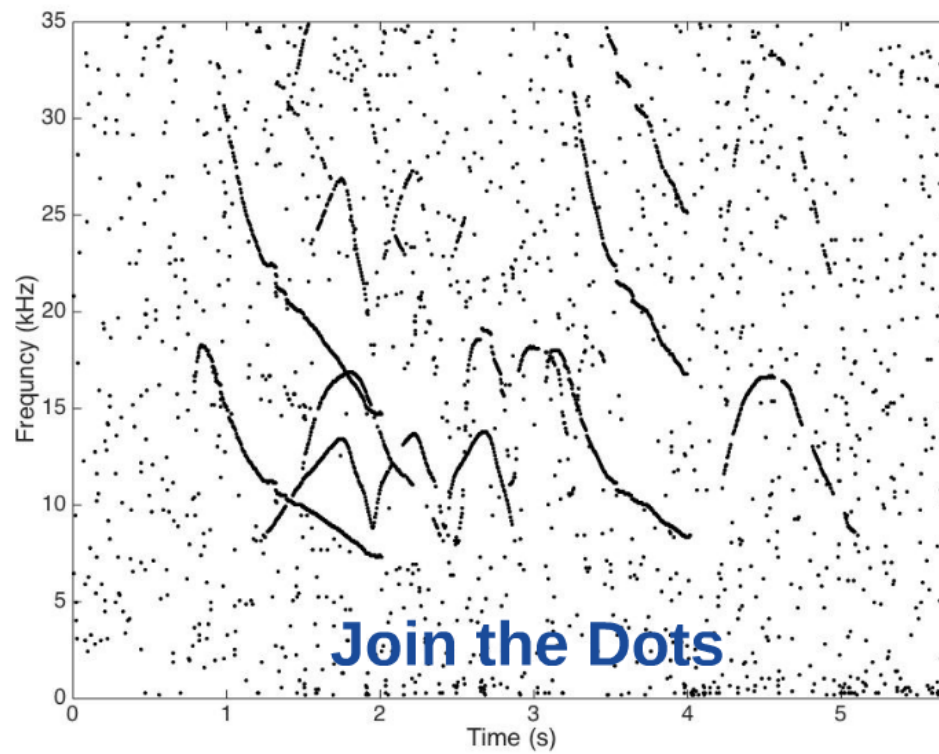
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Overview

- Target tracking
 - Single target tracking
 - Multi-target tracking
- PHD filter – GM-PHD filter
- GM-PHD application to synthetic and real data
- Challenges
- Conclusions

Problem description



Target tracking

Target: anything whose state is of interest

State: contains all information about the system under observation at a particular time

Measurement: output from a sensor (target + clutter)

Target tracking = the process of estimating a target's state from noisy measurements and linking together the detections from one source

2 models required

System (dynamic) model

$$x_k = Fx_{k-1} + Qv_{k-1}$$

Describes transformation of the state (x_k) with time

Measurement (observation) model

$$z_k = Hx_k + Rw_k$$

Describes how what we measure (z_k) relates to the state (x_k)

State space model for dolphin whistles

State

$$x_k = \begin{bmatrix} f \\ \alpha \end{bmatrix}^t$$

Current whistle frequency

Current whistle chirp rate

System model

$$x_k = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} x_{k-1} + v_{k-1}$$

Time between segments

System noise

Measurement model

$$z_k = \begin{bmatrix} 1 & 0 \end{bmatrix} x_k + w_k$$

We only measure frequency

Measurement noise

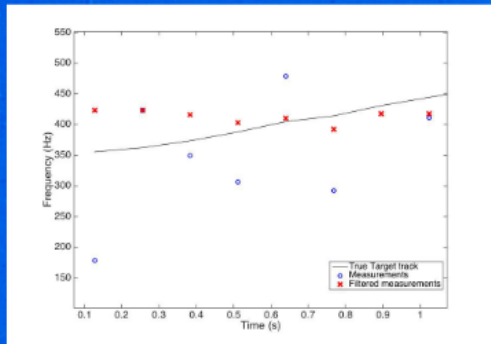
Single target tracking

- One target present, all measurements generated by target
- **Kalman filter**

$$\underbrace{x_k = Fx_{k-1} + Qv_{k-1}}_{\text{state}}$$

$$\underbrace{z_k = Hx_k + Rw_k}_{\text{measurement}}$$

Strict assumptions: linear models, Gaussian noise



$$\hat{x}_k = Fx_{k-1}$$

Predict state estimate

$$\hat{P}_k = Q + F P_{k-1} F^T$$

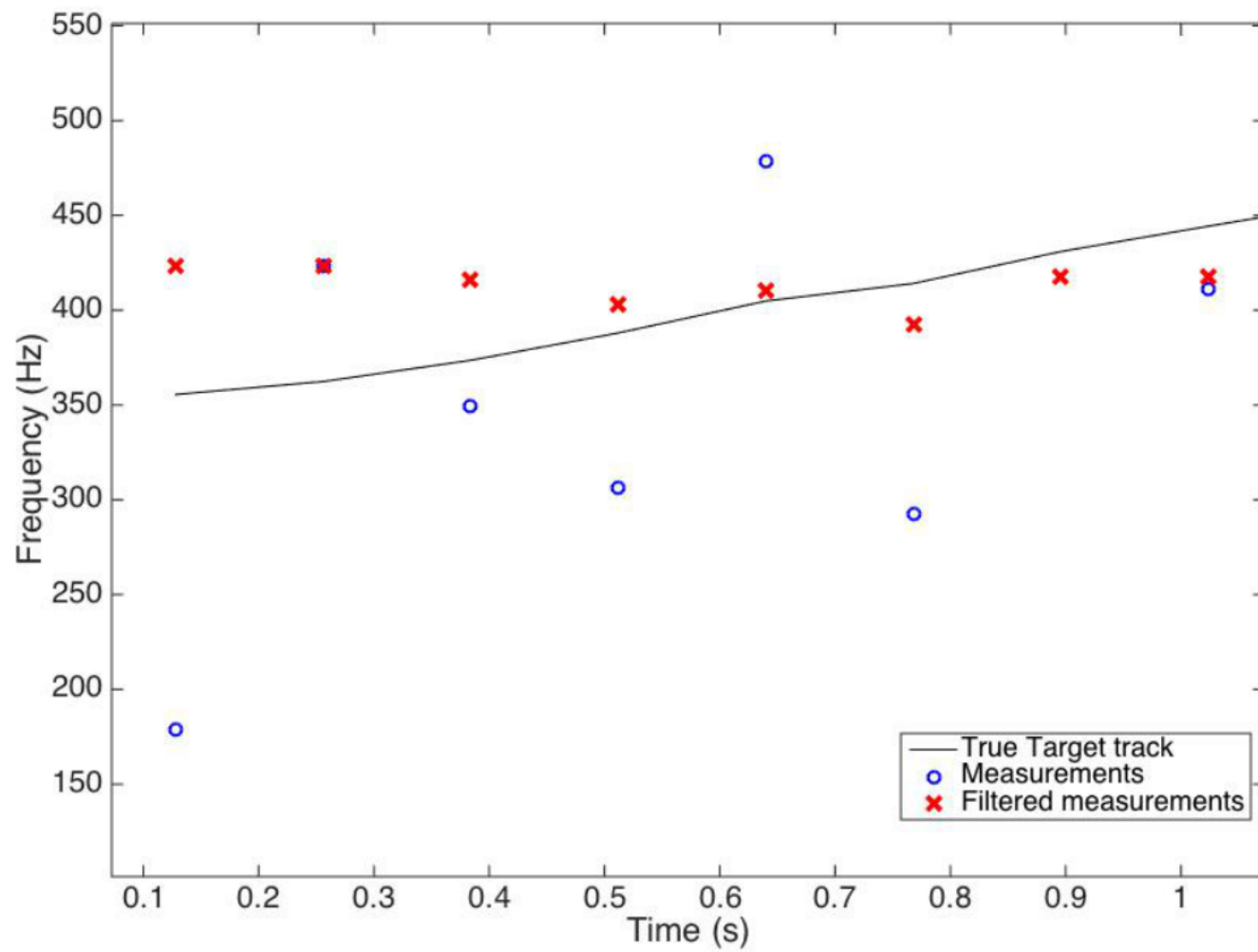
$$K = \hat{P}_k H^T (H \hat{P}_k H^T + R)^{-1}$$

Kalman gain

$$x_k = \hat{x}_k + K(z - H\hat{x}_k)$$

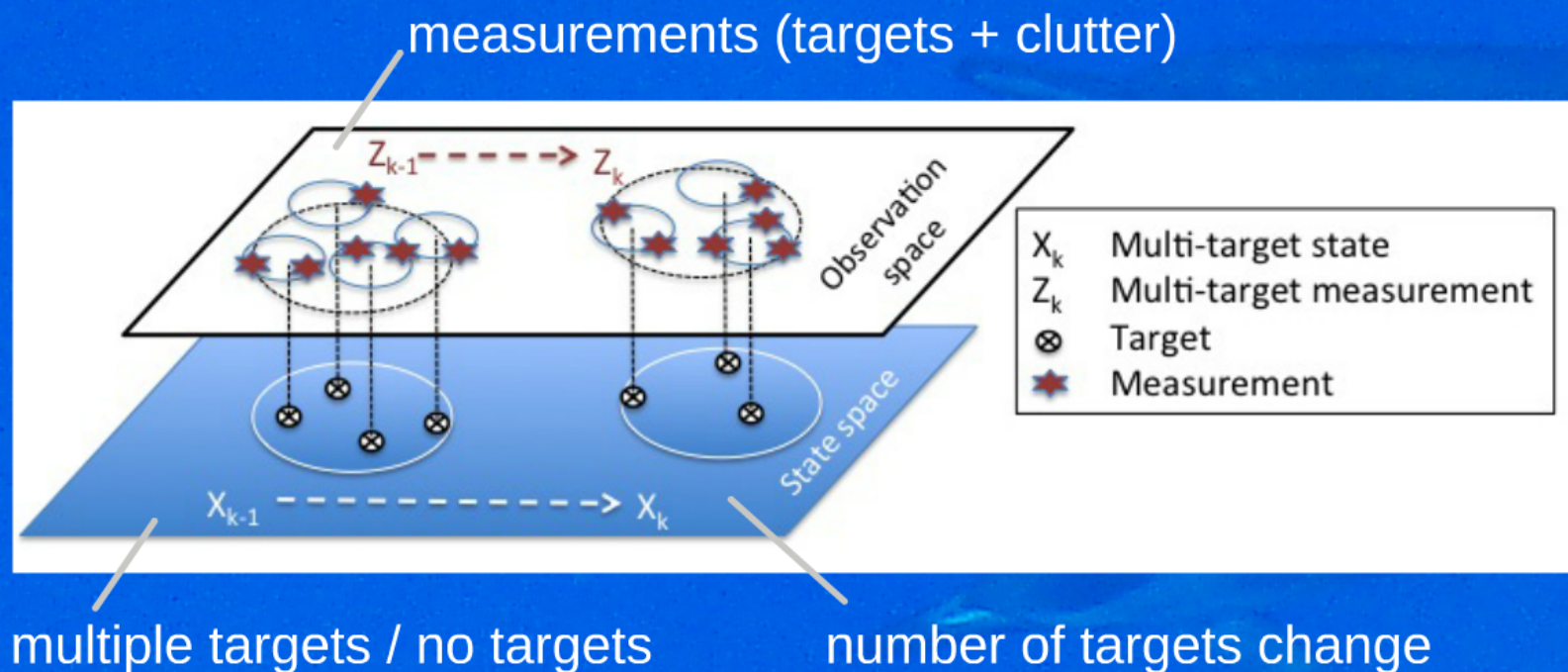
Update state estimate (refined)

$$P_k = (I - KH)\hat{P}_k$$



Multi-target tracking

Goal: jointly estimate the number of targets and their states from noisy measurements.



Traditional approaches: NN, GNN, JPDA, MHT;
others: FISST (PHD filters)

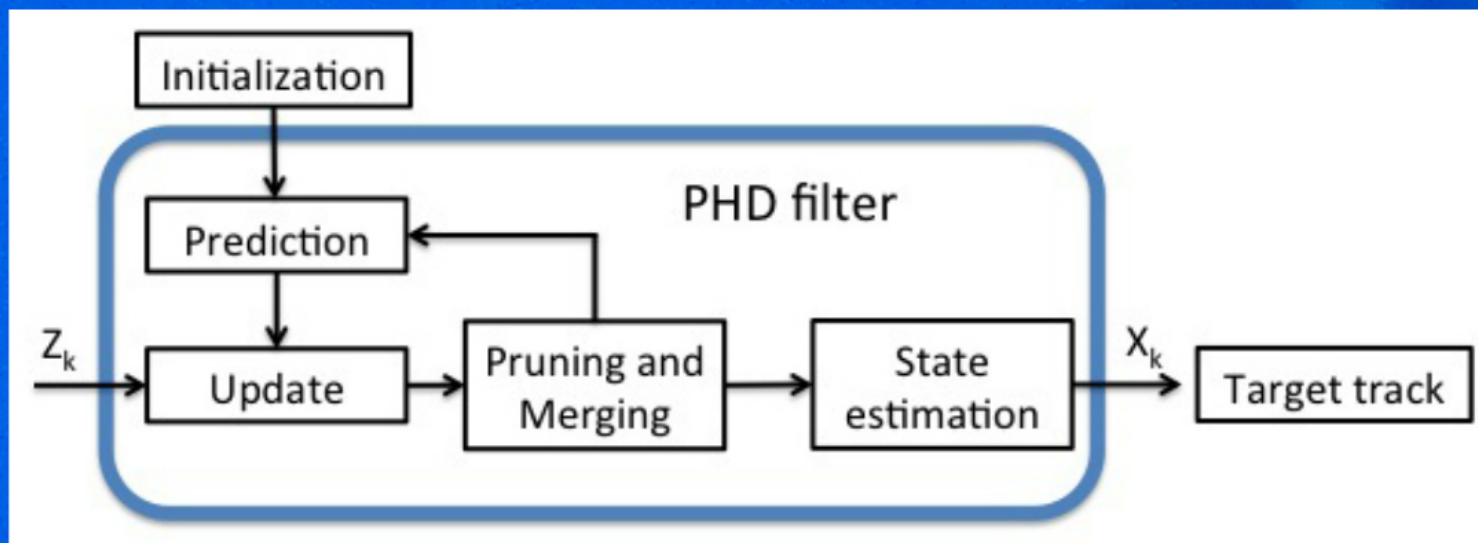
Probability Hypothesis Density (PHD) filters

- Based on Finite Set Statistics (FISST)

multi-source, multi-target problem

single-source, single-target problem

- Propagates first-order statistical moment (intensity function/PHD) – strategy analogous to Kalman filter



Gaussian Mixture PHD filter^[1]

- Approximates PHD filter
- Recursive algorithm, propagates intensity function or PHD that is represented by a sum of weighted Gaussian components

Each target \approx Gaussian component



Means and covariances
predicted & updated with
Kalman filter equations

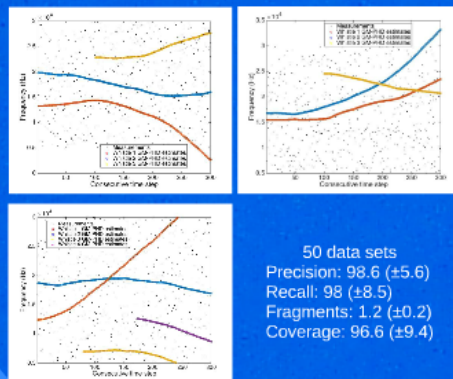


Weights
predicted & updated with
PHD equation

- Assumptions: linear Gaussian system and measurement models

GM-PHD filter applications

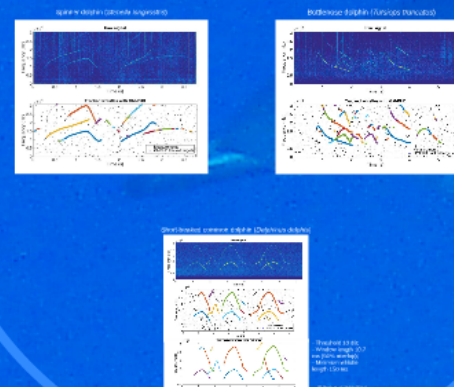
Synthetic data



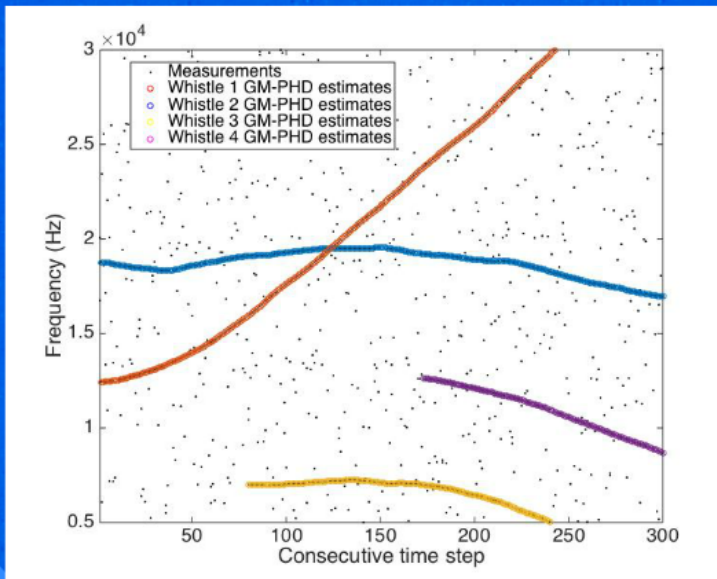
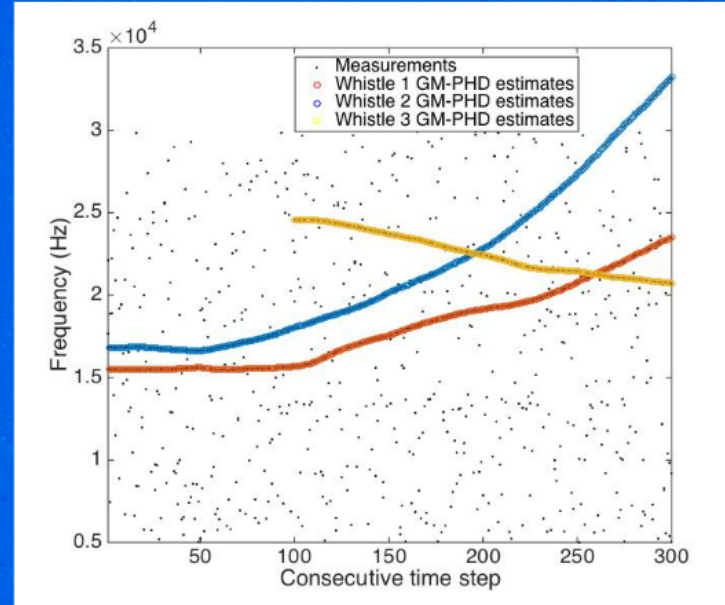
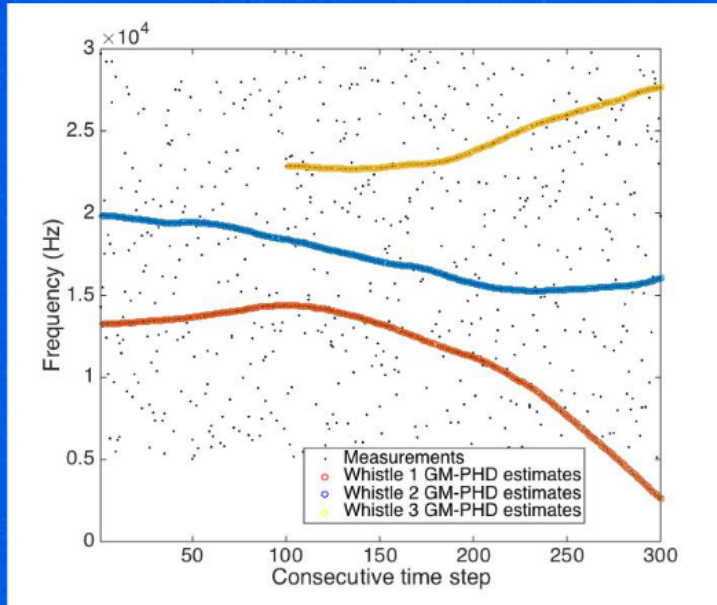
50 data sets
Precision: 98.6 (± 5.6)
Recall: 98 (± 8.5)
Fragments: 1.2 (± 0.2)
Coverage: 96.6 (± 9.4)

Real data

(data taken from MobySound.org)



Synthetic data

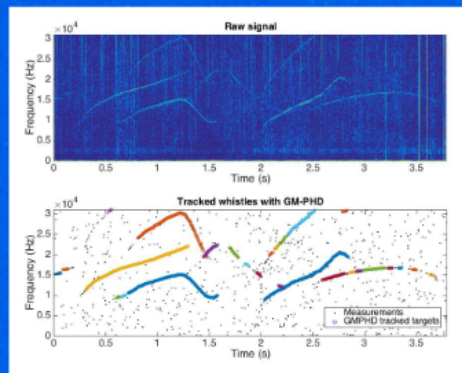


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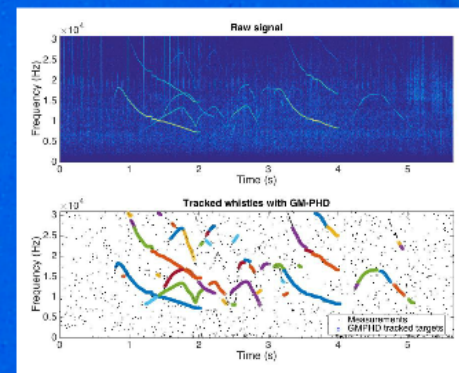
Real data

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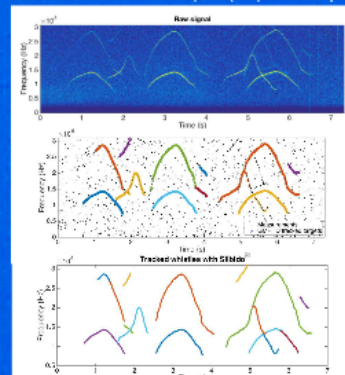
Spinner dolphin (*Stenella longirostris*)



Bottlenose dolphin (*Tursiops truncatus*)



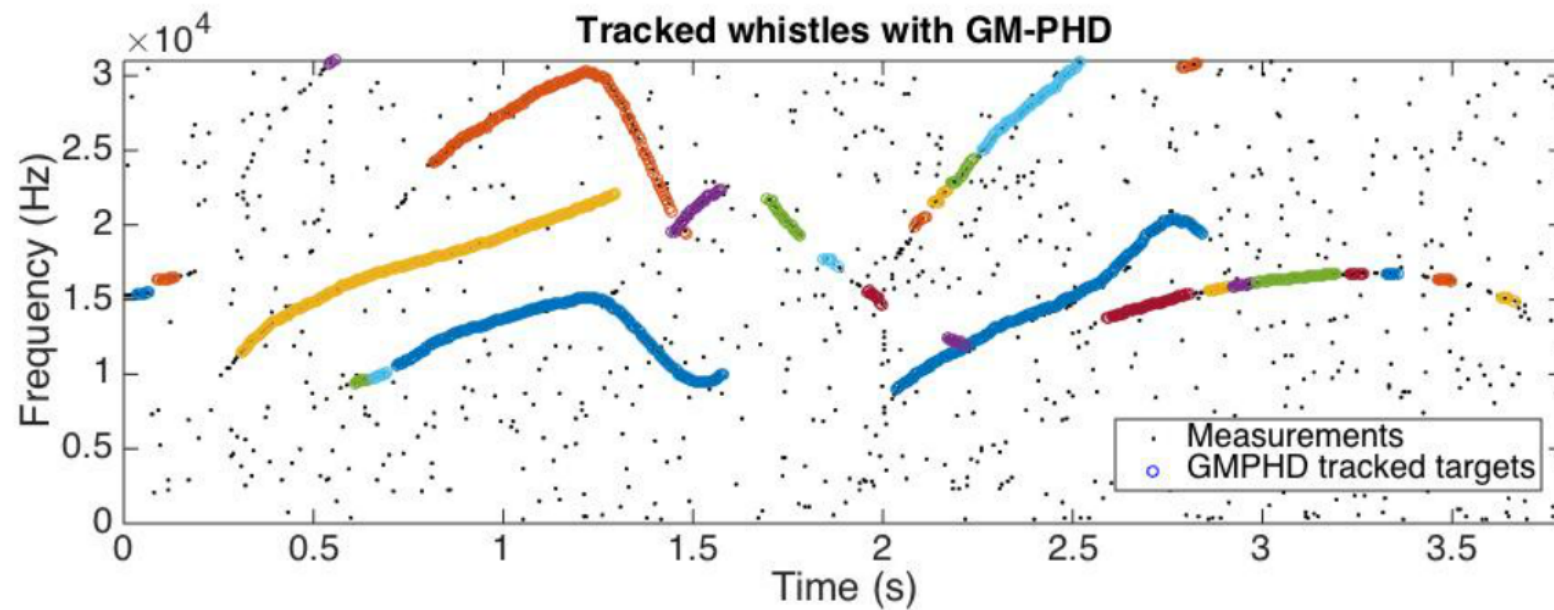
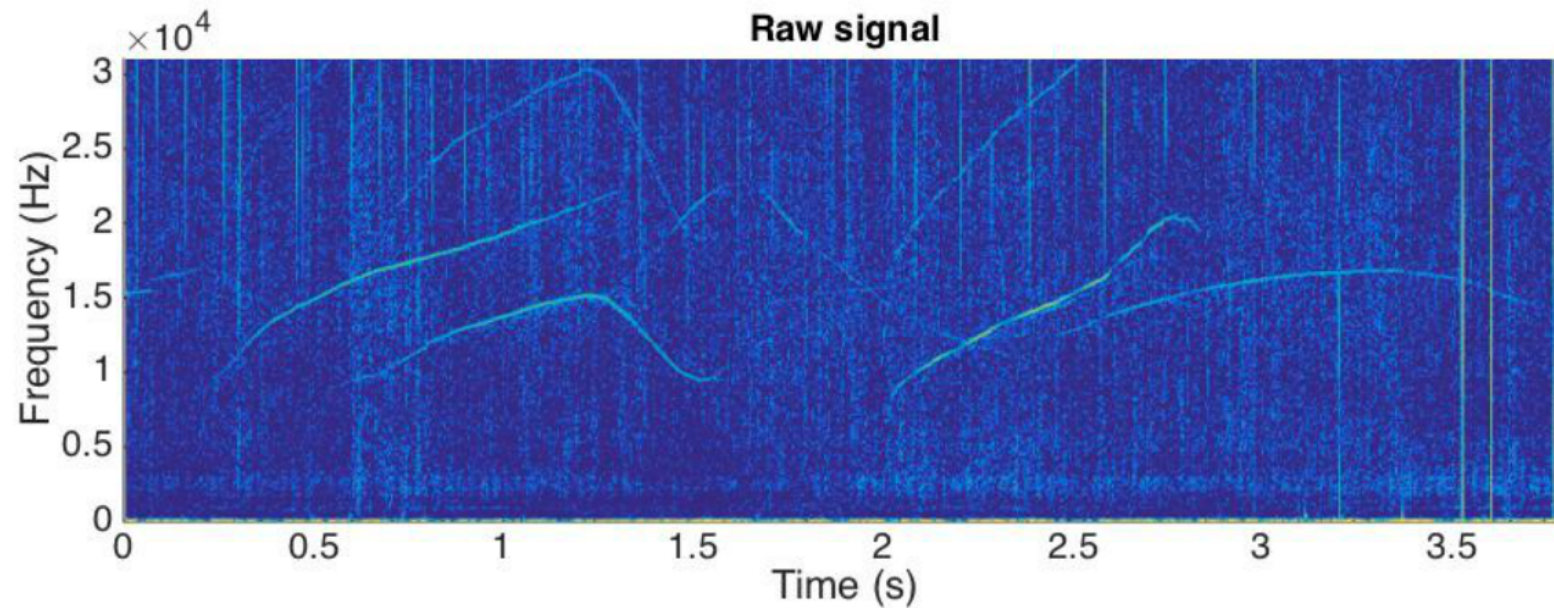
Short-beaked common dolphin (*Delphinus delphis*)



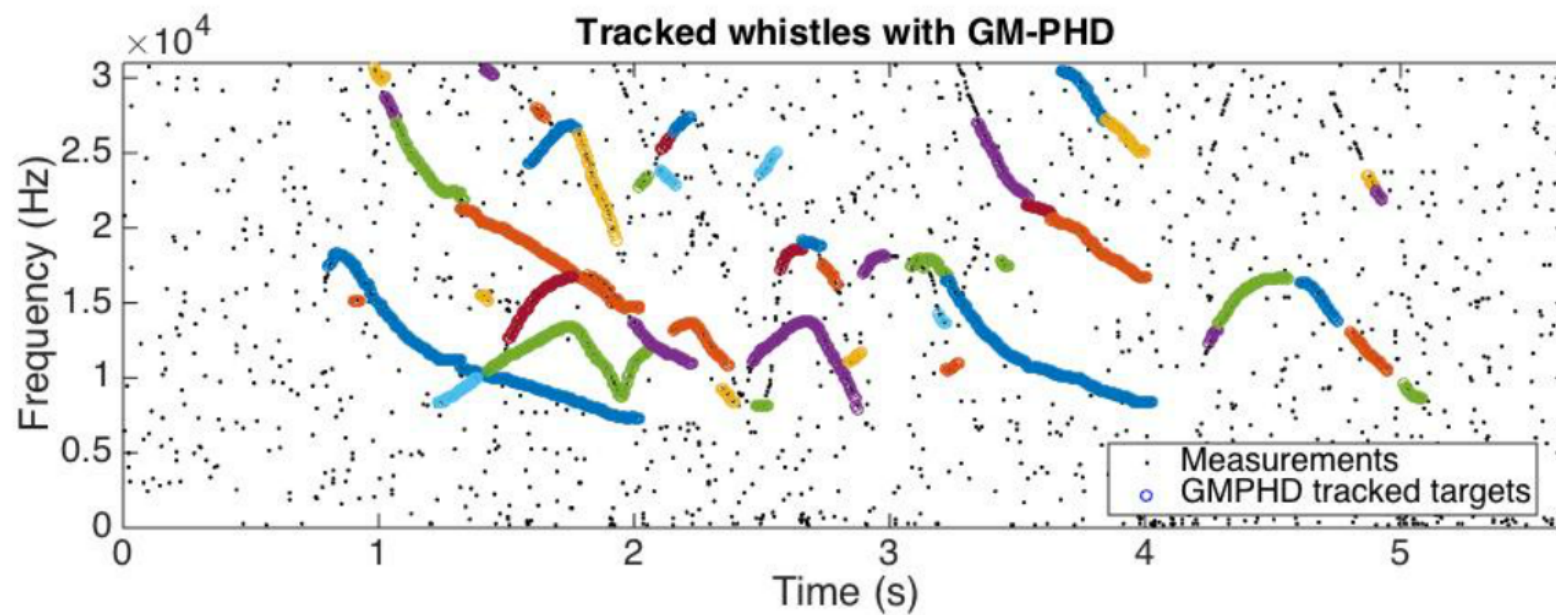
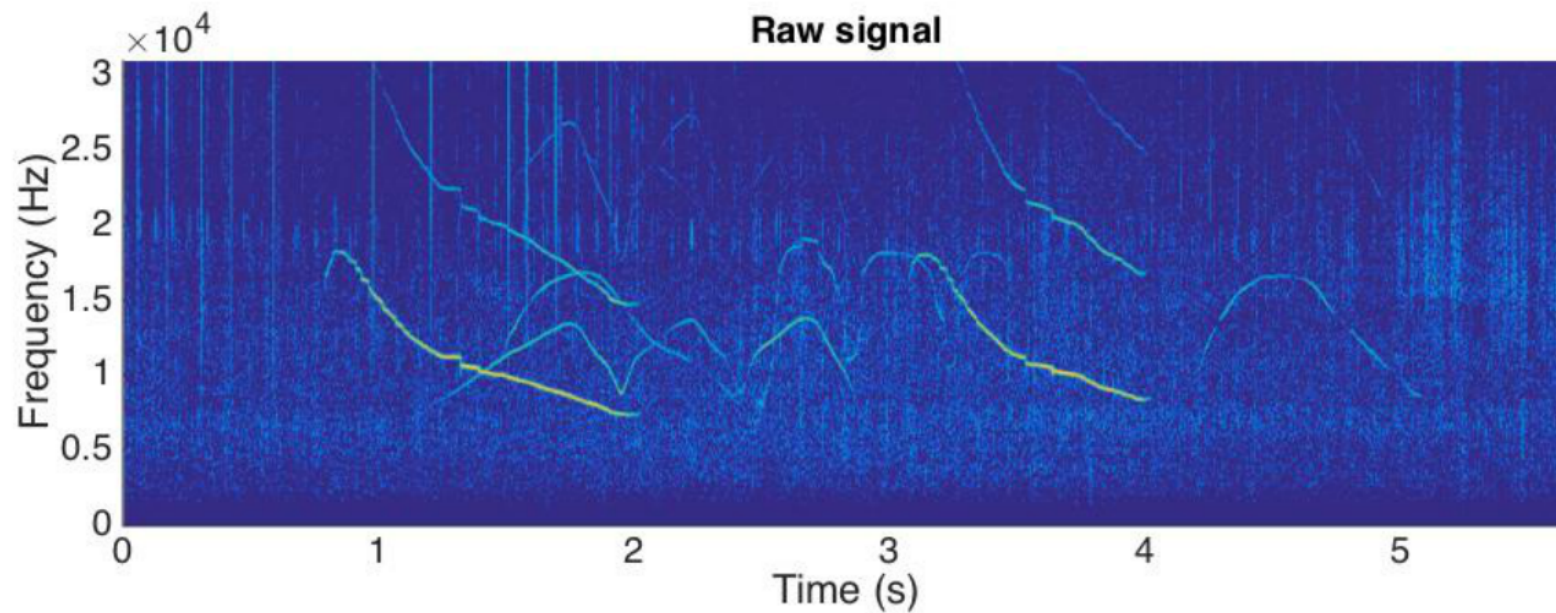
- Threshold 10 dB;
- Window length 10.7 ms (50% overlap);
- Minimum whistle length 150 ms.

[2] Roch et al. JASA (2011)

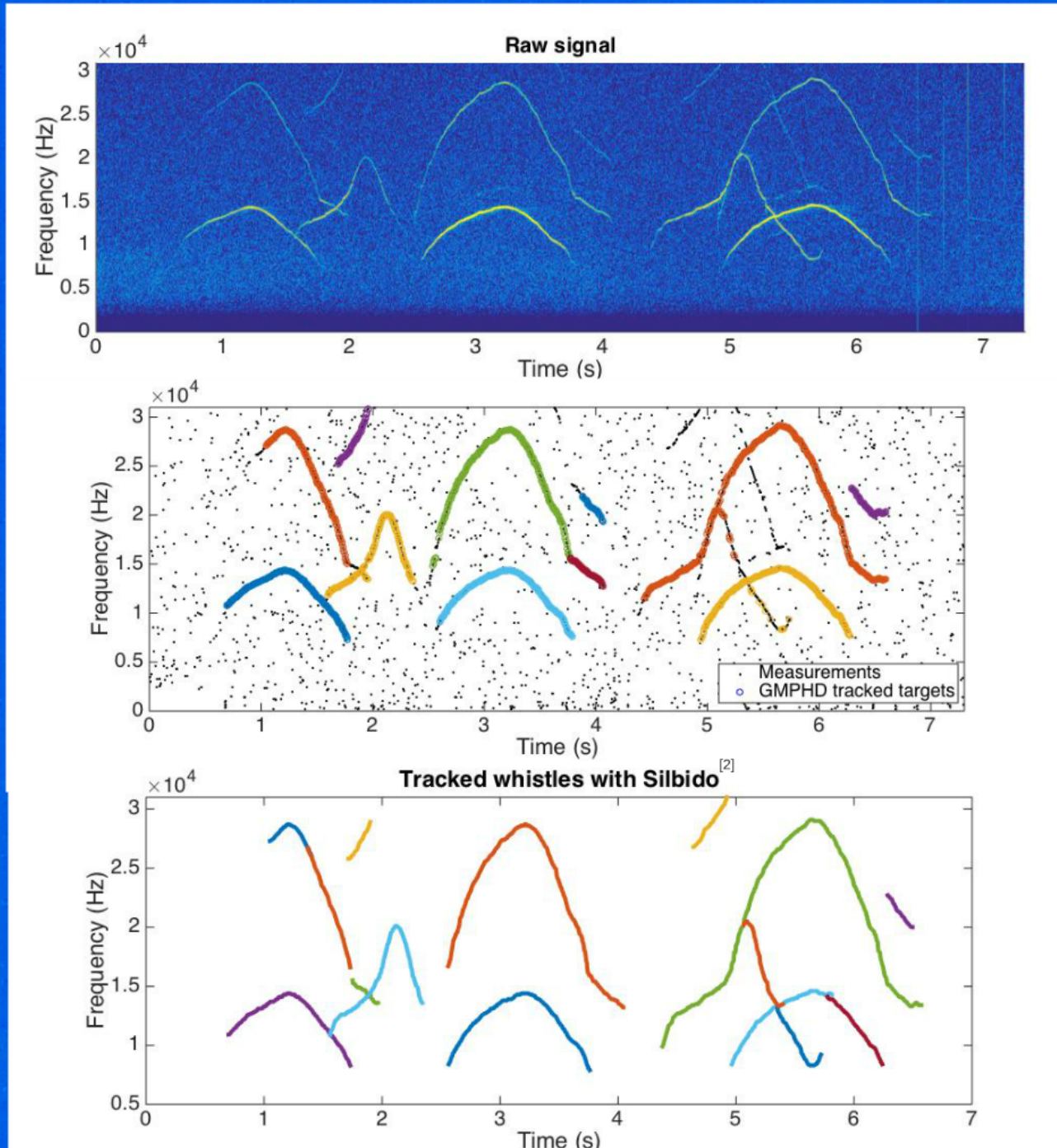
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Challenges

- Optimization of GM-PHD filter parameters
- Models (system, measurement, birth and clutter)
- Assumes linear models

PSEUDO-CODE FOR THE GAUSSIAN MIXTURE PHD FILTER.	PRUNING FOR THE GAUSSIAN MIXTURE PHD FILTER.
<p>given $\{w_{k-1}^{(i)}, m_{k-1}^{(i)}, P_{k-1}^{(i)}\}_{i=1}^{J_{k-1}}$, and the measurement set Z_k.</p> <p>step 1. (prediction for birth targets)</p> <p>$i := 0$.</p> <p>for $j = 1, \dots, J_{\gamma,k}$</p> <p>$i := i + 1$.</p> <p>$w_{k k-1}^{(i)} = w_{\gamma,k}^{(j)}$, $m_{k k-1}^{(i)} = m_{\gamma,k}^{(j)}$, $P_{k k-1}^{(i)} = P_{\gamma,k}^{(j)}$.</p> <p>end</p> <p>for $j = 1, \dots, J_{\beta,k}$</p> <p>for $\ell = 1, \dots, J_{k-1}$</p> <p>$i := i + 1$.</p> <p>$w_{k k-1}^{(i)} = w_{k-1}^{(\ell)} w_{\beta,k}^{(j)}$,</p> <p>$m_{k k-1}^{(i)} = d_{\beta,k-1}^{(j)}$,</p> <p>$P_{k k-1}^{(i)} = Q_{\beta,k-1}^{(j)}$.</p> <p>end</p> <p>end</p> <p>step 2. (prediction for existing targets)</p> <p>for $j = 1, \dots, J_{k-1}$</p> <p>$i := i + 1$.</p> <p>$w_{k k-1}^{(i)} = PS_{k,k} w_{k-1}^{(j)}$,</p> <p>$m_{k k-1}^{(i)} = F_{k-1} m_{k-1}^{(j)}$, $P_{k k-1}^{(i)} = Q_{k-1} + F_{k-1} P_{k-1}^{(j)} F_{k-1}^T$.</p> <p>end</p> <p>$J_{k k-1} = i$.</p> <p>step 3. (construction of PHD up to $J_{k k-1}$ components)</p> <p>for $j = 1, \dots, J_{k k-1}$</p> <p>$\eta_{k k-1}^{(j)} = H_k m_{k k-1}^{(j)}$,</p> <p>$K_k^{(j)} = P_{k k-1}^{(j)} H_k^T (S_k^{(j)})^{-1}$.</p> <p>end</p> <p>step 4. (update)</p> <p>for $j = 1, \dots, J_{k k-1}$</p> <p>$w_k^{(j)} = (1 - PD_{k,k}) w_{k k-1}^{(j)}$,</p> <p>$m_k^{(j)} = m_{k k-1}^{(j)}$, $P_k^{(j)} = P_{k k-1}^{(j)}$.</p> <p>end</p> <p>$\ell := 0$.</p> <p>for each $z \in Z_k$</p> <p>$\ell := \ell + 1$.</p> <p>for $j = 1, \dots, J_{k k-1}$</p> <p>$w_k^{(\ell J_{k k-1} + j)} = PD_{k,k} w_{k k-1}^{(j)} \mathcal{N}(z; \eta_{k k-1}^{(j)}, S_k^{(j)})$,</p> <p>$m_k^{(\ell J_{k k-1} + j)} = m_{k k-1}^{(j)} + K_k^{(j)} (z - \eta_{k k-1}^{(j)})$,</p> <p>$P_k^{(\ell J_{k k-1} + j)} = P_{k k-1}^{(j)}$.</p> <p>end</p> <p>$w_k^{(\ell J_{k k-1} + j)} := \frac{w_k^{(\ell J_{k k-1} + j)}}{\sum_{i=1}^{J_k} w_k^{(i)}}$, for $j = 1, \dots, J_{k k-1}$.</p> <p>end</p> <p>$J_k = \ell J_{k k-1} + J_{k k-1}$.</p> <p>output $\{w_k^{(i)}, m_k^{(i)}, P_k^{(i)}\}_{i=1}^{J_k}$.</p>	<p>given $\{w_k^{(i)}, m_k^{(i)}, P_k^{(i)}\}_{i=1}^{J_k}$, a truncation threshold T, a merging threshold U, and a maximum allowable number of Gaussian terms J_{max}.</p> <p>Set $\ell = 0$, and $I = \{i = 1, \dots, J_k w_k^{(i)} > T\}$.</p> <p>repeat</p> <p>$\ell := \ell + 1$.</p> <p>$j := \arg \max_{i \in I} w_k^{(i)}$.</p> <p>$L := \{i \in I (m_k^{(i)} - m_k^{(j)})^T (P_k^{(i)})^{-1} (m_k^{(i)} - m_k^{(j)}) \leq U\}$.</p> <p>$\tilde{w}_k^{(\ell)} = \sum_{i \in L} w_k^{(i)}$.</p> <p>$\tilde{m}_k^{(\ell)} = \frac{1}{\tilde{w}_k^{(\ell)}} \sum_{i \in L} w_k^{(i)} x_k^{(i)}$.</p> <p>$\tilde{P}_k^{(\ell)} = \frac{1}{\tilde{w}_k^{(\ell)}} \sum_{i \in L} w_k^{(i)} (P_k^{(i)} + (\tilde{m}_k^{(\ell)} - m_k^{(i)}) (\tilde{m}_k^{(\ell)} - m_k^{(i)})^T)$.</p> <p>$I := I \setminus L$.</p> <p>until $I = \emptyset$.</p> <p>if $\ell > J_{max}$ then replace $\{\tilde{w}_k^{(i)}, \tilde{m}_k^{(i)}, \tilde{P}_k^{(i)}\}_{i=1}^{\ell}$ by those of the J_{max} Gaussians with largest weights.</p> <p>output $\{\tilde{w}_k^{(i)}, \tilde{m}_k^{(i)}, \tilde{P}_k^{(i)}\}_{i=1}^{\ell}$ as pruned Gaussian components.</p>
	<p>TABLE III</p> <p>MULTI-TARGET STATE EXTRACTION</p> <p>given $\{w_k^{(i)}, m_k^{(i)}, P_k^{(i)}\}_{i=1}^{J_k}$.</p> <p>Set $\hat{X}_k = \emptyset$.</p> <p>for $i = 1, \dots, J_k$</p> <p>if $w_k^{(i)} > 0.5$</p> <p>for $j = 1, \dots, \text{round}(w_k^{(i)})$</p> <p>update $\hat{X}_k := [\hat{X}_k, m_k^{(i)}]$</p> <p>end</p> <p>end</p> <p>output \hat{X}_k as the multi-target state estimate.</p>

Conclusions

- Successfully implemented automated MTT using GM-PHD filters
 - Synthetic problems (works very well)
 - Real data (occasional “breaking” of contours occurs)
- GM-PHD filter shows considerable promise to simultaneously track whistle contours
- Filter fast and computationally reasonable

Future work

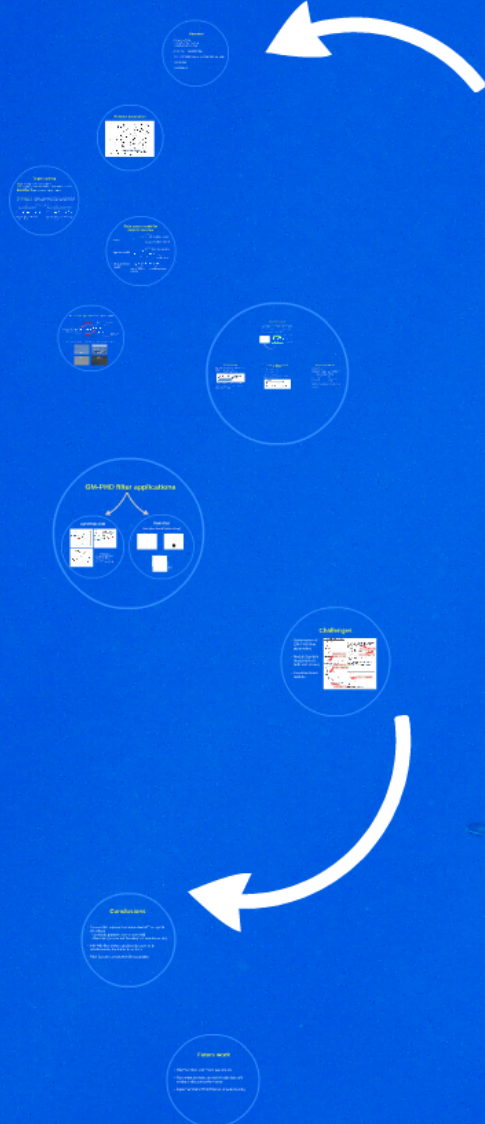
- Optimize filter and model parameters
- Run extensive tests on real whistle data and evaluate detector performance
- Implement SMC-PHD filter for whistle tracking

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Thank you!
Any Questions?