Institute of Sound
and Vibration Research

UNIVERSITY OF Southampton

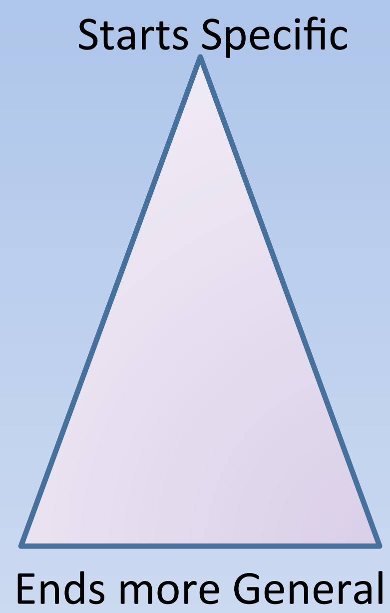
Tracking Algorithms in Marine Mammal Acoustics

(Trying to untangle the spaghetti)

Paul White

Acknowledgements:
The main workers: Mark Hadley, Imtiaz Ahmed
Other co-workers: Doug Gillespie, Marjolaine Caillat, Jonathan Gordon (Dolphins)
3S team: TNO, FOI, St Andrews (Sperm whales)

Talk Outline



- Problem description(s)
  - Dolphin Whistles
  - Sperm Whale tracking
- State space representations
- Single target tracking
  - Kalman filter
  - Extended Kalman filter; Unscented Kalman filter
  - Particle filter
- Multi-target tracking
  - Multiple Hypothesis Tracker
  - Probability Hypothesis Density Filter
- Results

What do I mean by Tracking?

UPS OnLine® Tools - Tracking Results

Ship to Address
40 Tum A Lum Cir
Westerly, RI
US

Ship From Address
80 Micro Dr
Jonestown, PA
US

Tracking Number: 1Z1836814276886243
Shipped on date: 05/19/2003 via GROUND
Number of pkgs in shipment: 1 **Package Weight:** 3.00 LBS
Scheduled delivery date: 05/21/2003

Date	Time	Location	Activity
05/22/2003	9:06 am	Westerly, RI (US)	DELIVERED
05/21/2003	8:28 am	Warwick, RI (US)	OUT FOR DELIVERY
05/21/2003	2:52 am	Warwick, RI (US)	ARRIVAL SCAN
05/21/2003	1:11 am	Chelmsford, MA (US)	DEPARTURE SCAN
05/20/2003	4:38 pm	Chelmsford, MA (US)	LOCATION SCAN
05/20/2003	1:14 pm	Chelmsford, MA (US)	ARRIVAL SCAN
05/20/2003	7:10 am	Saddle Brook, NJ (US)	DEPARTURE SCAN
05/20/2003	4:31 am	Saddle Brook, NJ (US)	ARRIVAL SCAN
05/19/2003	9:02 pm	Lancaster, PA (US)	DEPARTURE SCAN
05/19/2003	4:58 pm	Lancaster, PA (US)	ORIGIN SCAN
05/19/2003	6:06 am	-----, ----- (US)	BILLING INFORMATION RECEIVED

- Linking together (associating) isolated detections from one (acoustic) source.
  - This may correspond to physical space, e.g. following an animal as it moves, but not necessarily.

Example Applications

- Dolphin whistles

(See Doug's and Harry's talk yesterday)

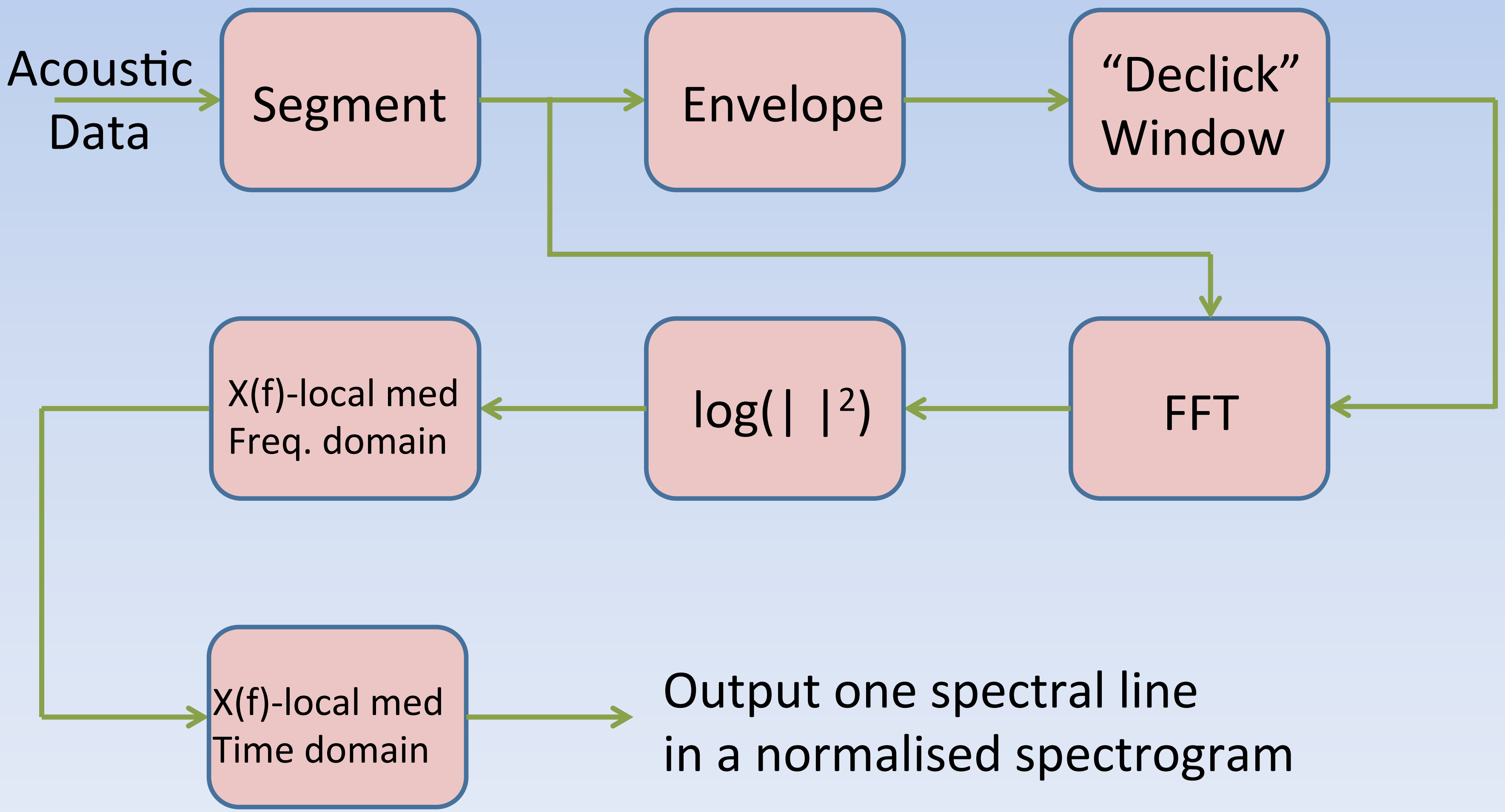
  - Passive acoustic monitoring:
    - Potential for species ID
    - Recognition of individual (signature whistles)?
  - Tools to understand behaviours, acoustic repertoires, etc.

- Tracking sperm whales

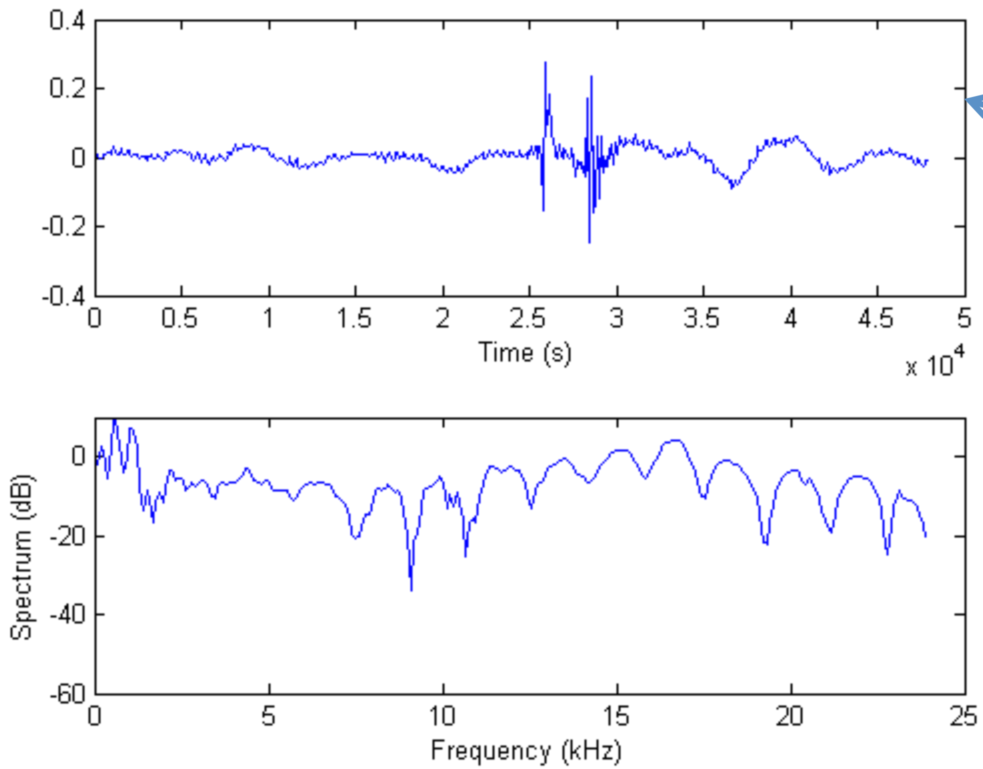
(See Walter, Herve, Michel, Gianni + co-workers, Doug ……)

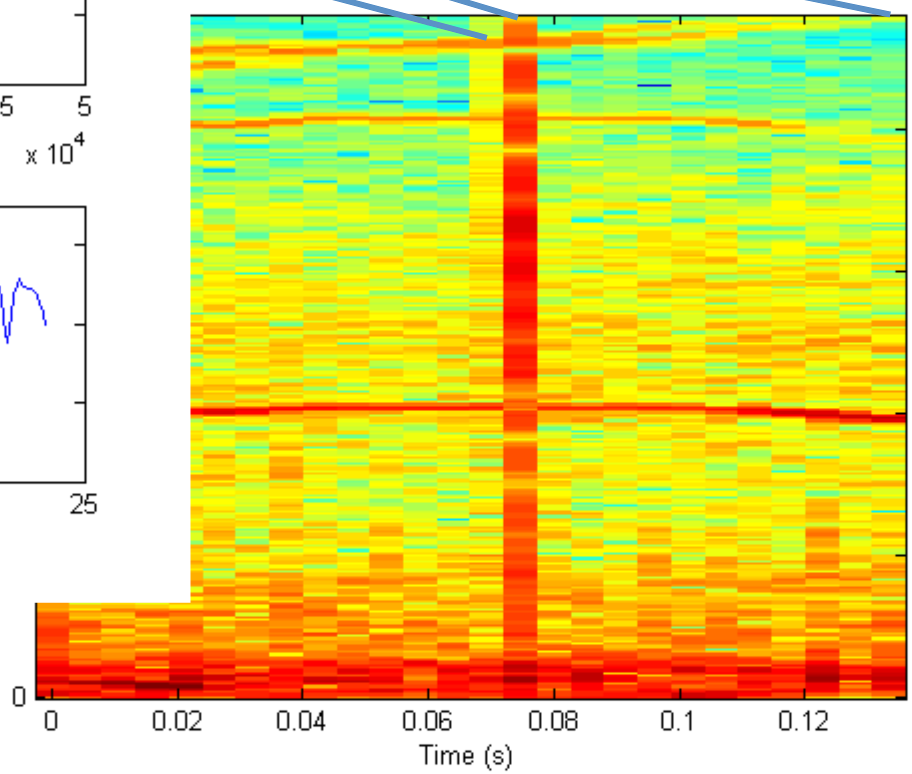
  - Following individuals, e.g. during controlled exposure experiments.
  - Population surveys

Dolphin Whistle Detection



Example: “The Problem with Clicks”





Declicking Window

Controls sharpness of cut-off (e.g. 3)

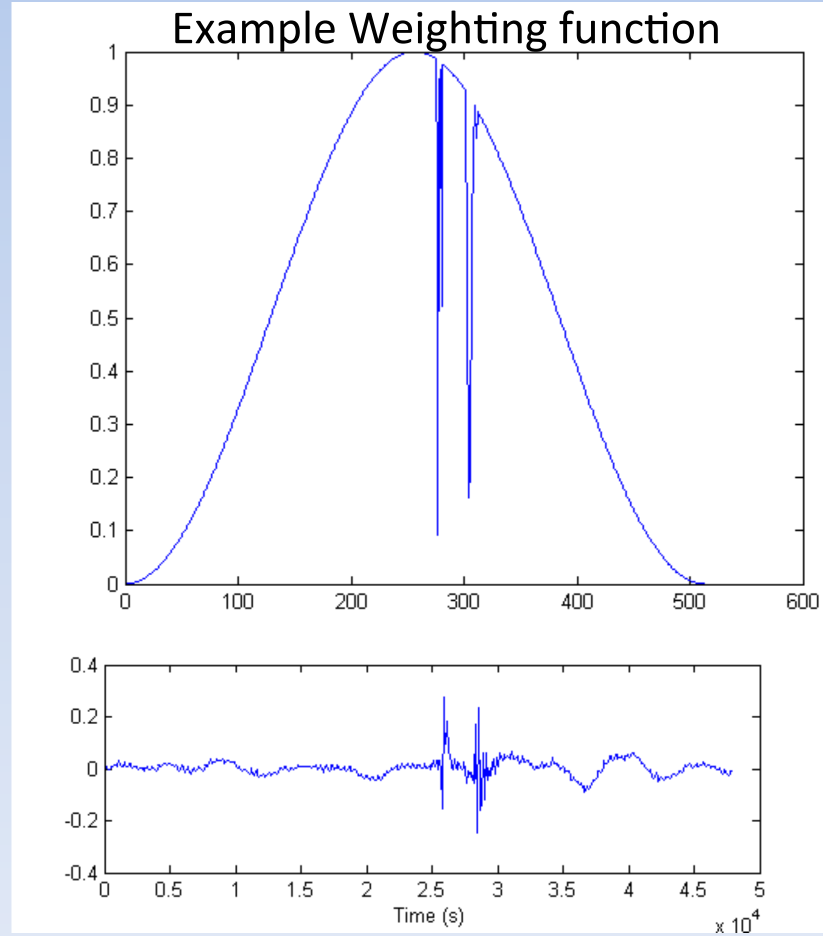
$$w(n) = \frac{1}{1 + \left(\frac{x(n)}{T\sigma} \right)^{2\alpha}} h(n)$$

Threshold (e.g. 5)

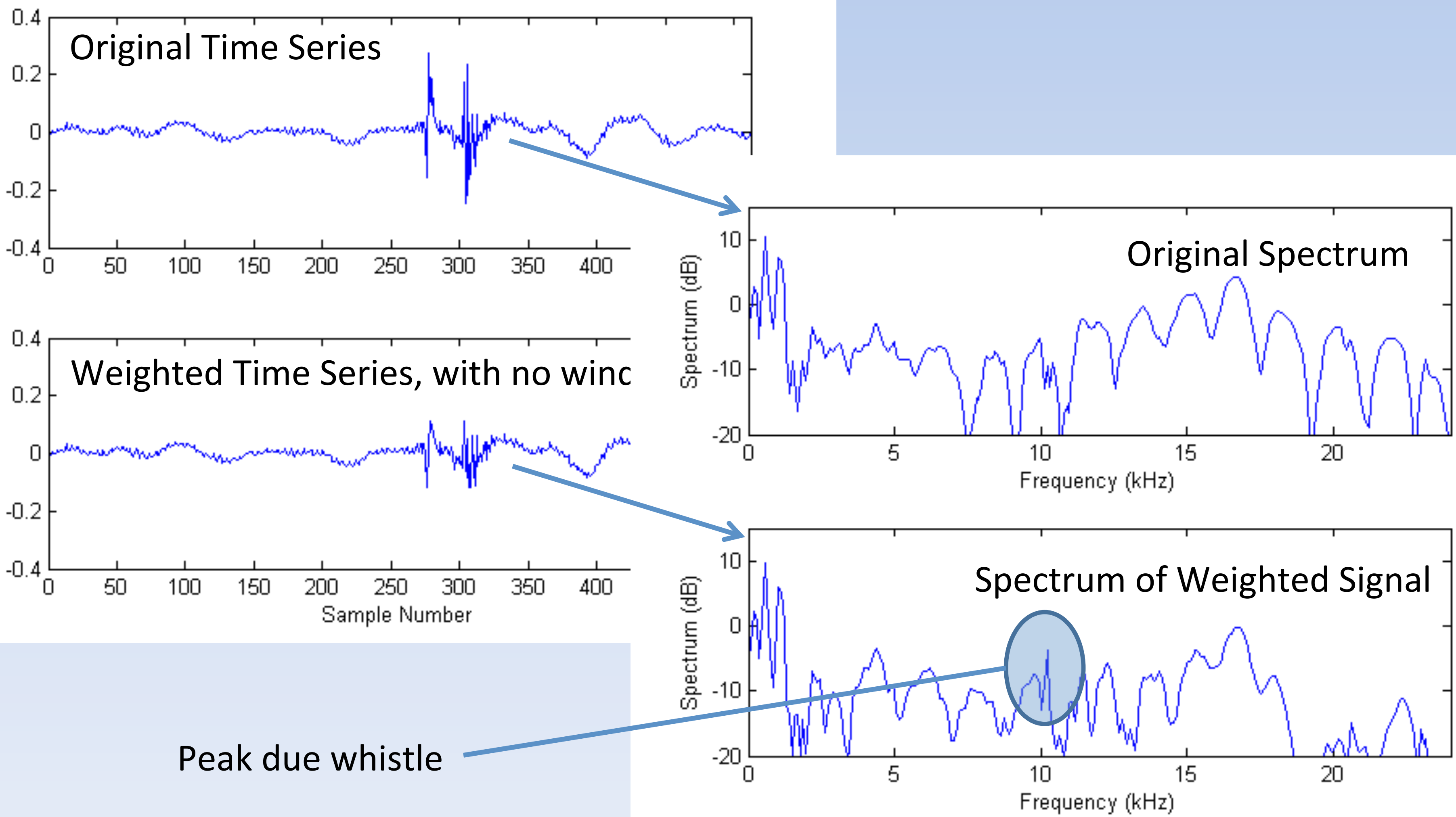
Std. Dev. in the segment

Classical spectral window

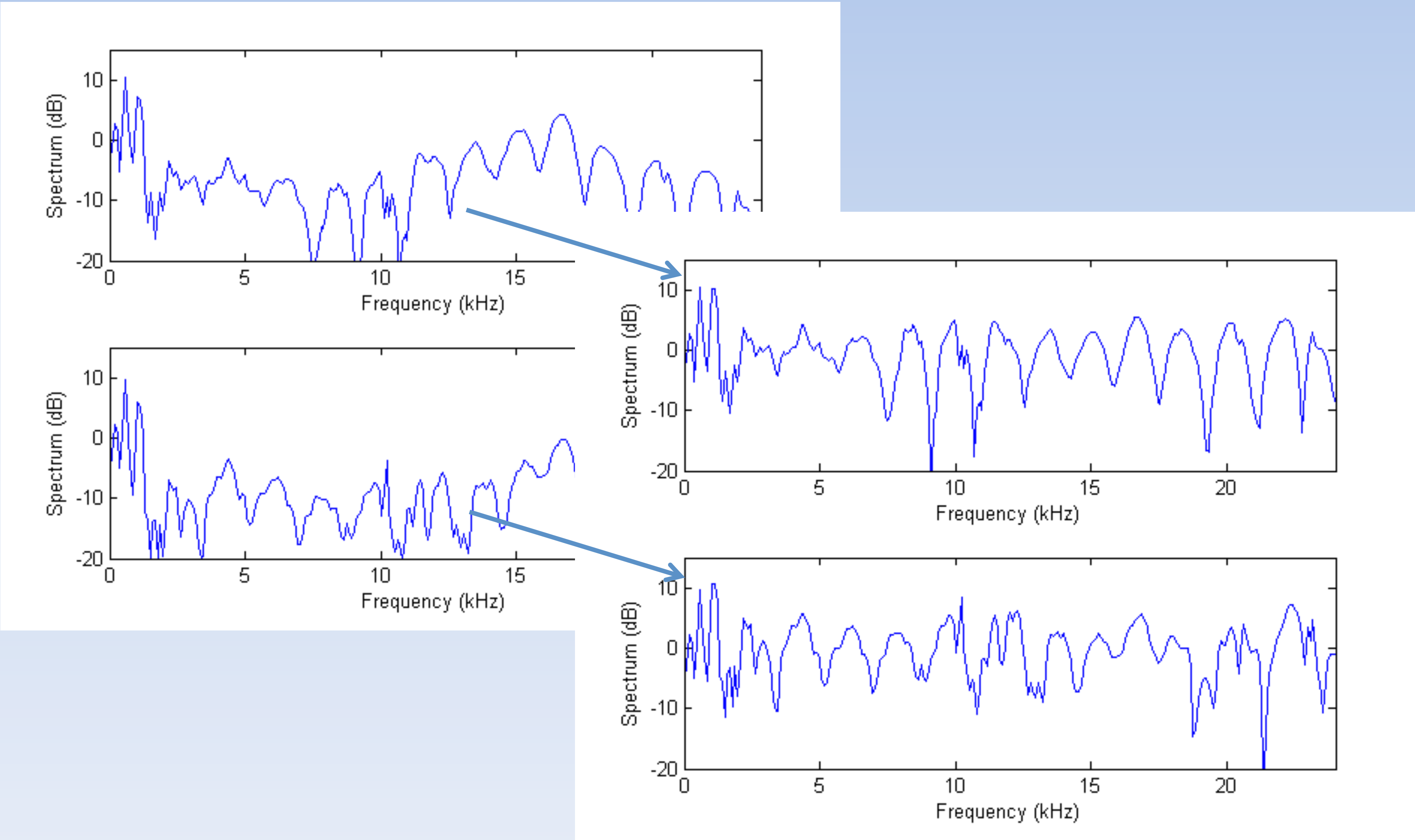
$$S(k) = \left| FFT\left\{ w(n)\, x(n) \right\} \right|^2$$



Declicking in Action
Analysis of One Frame

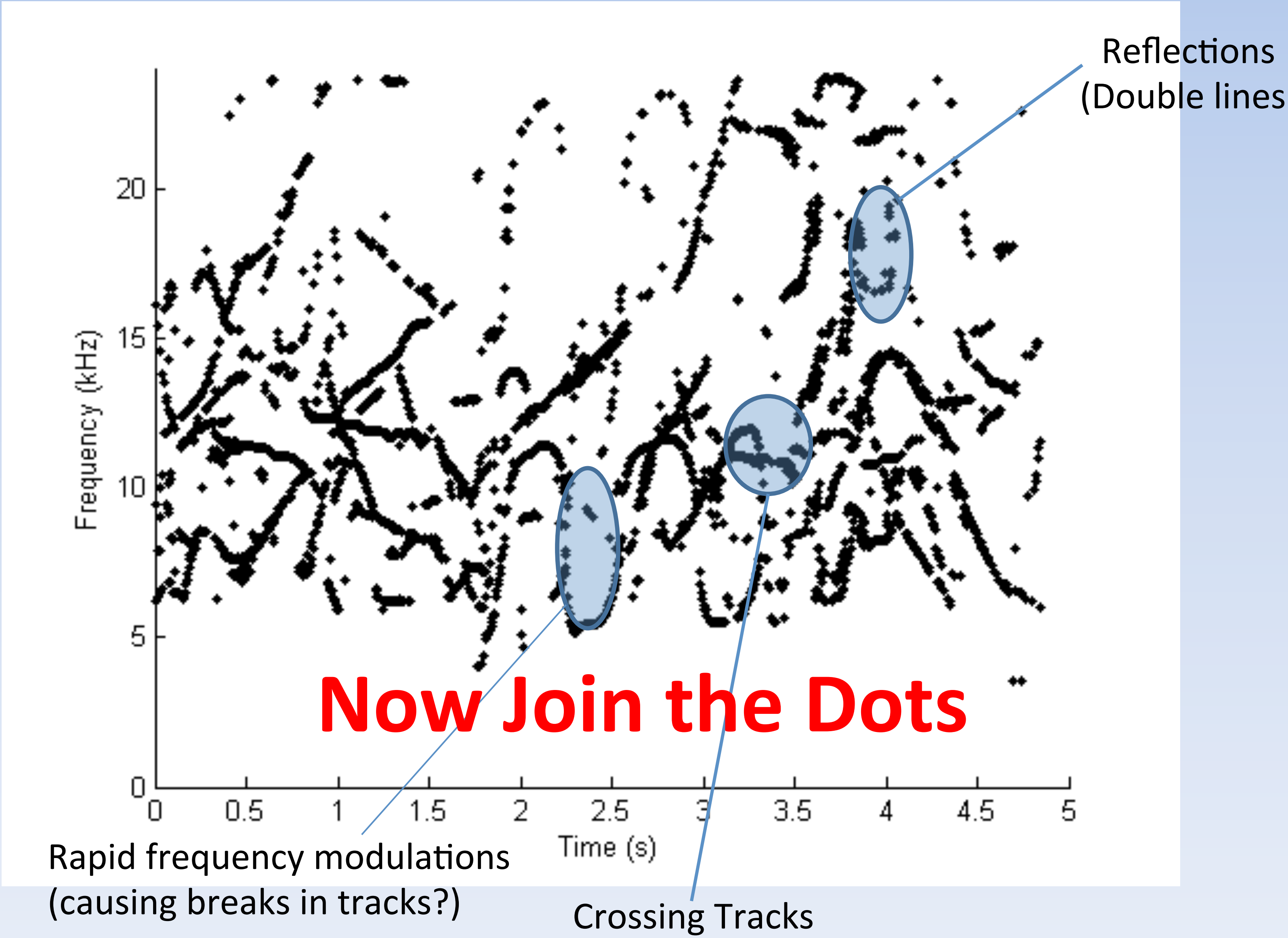


Applying the Median Filter in Frequency



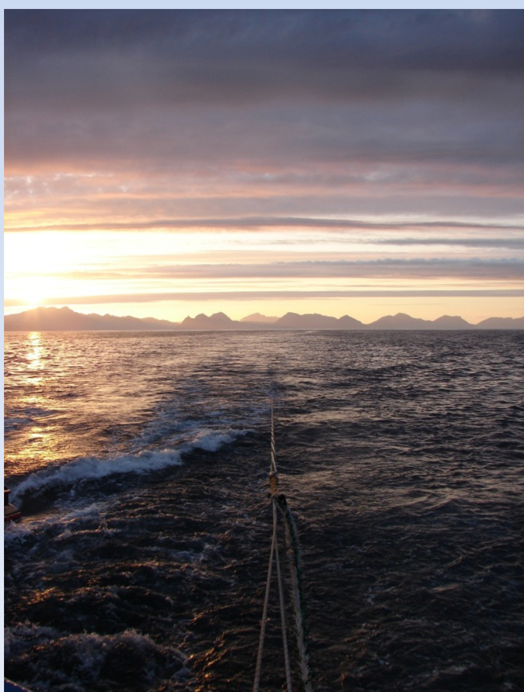
Dolphin Whistle Example

Common Dolphin (*Delphinus delphis*)

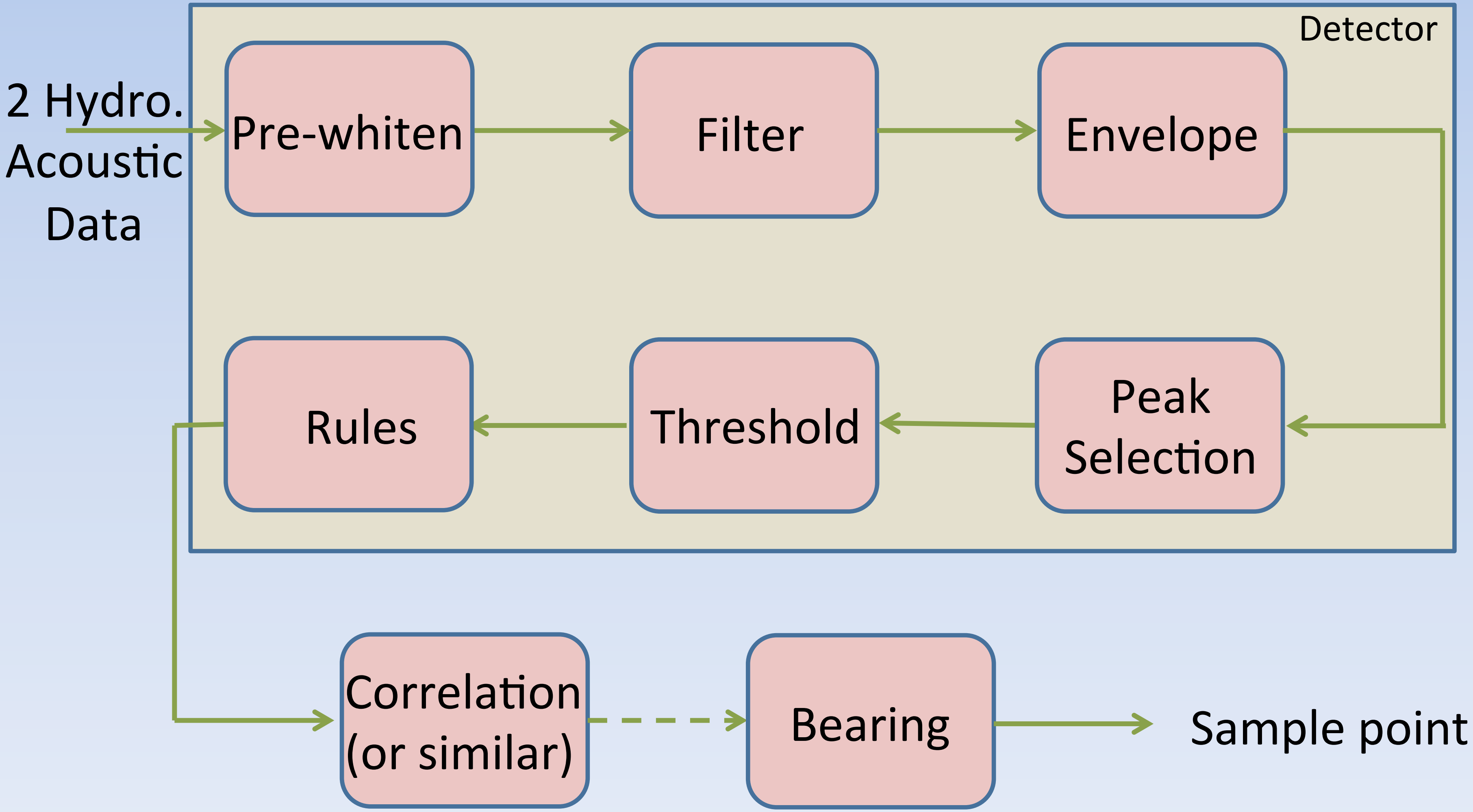


Sperm Whale Tracking

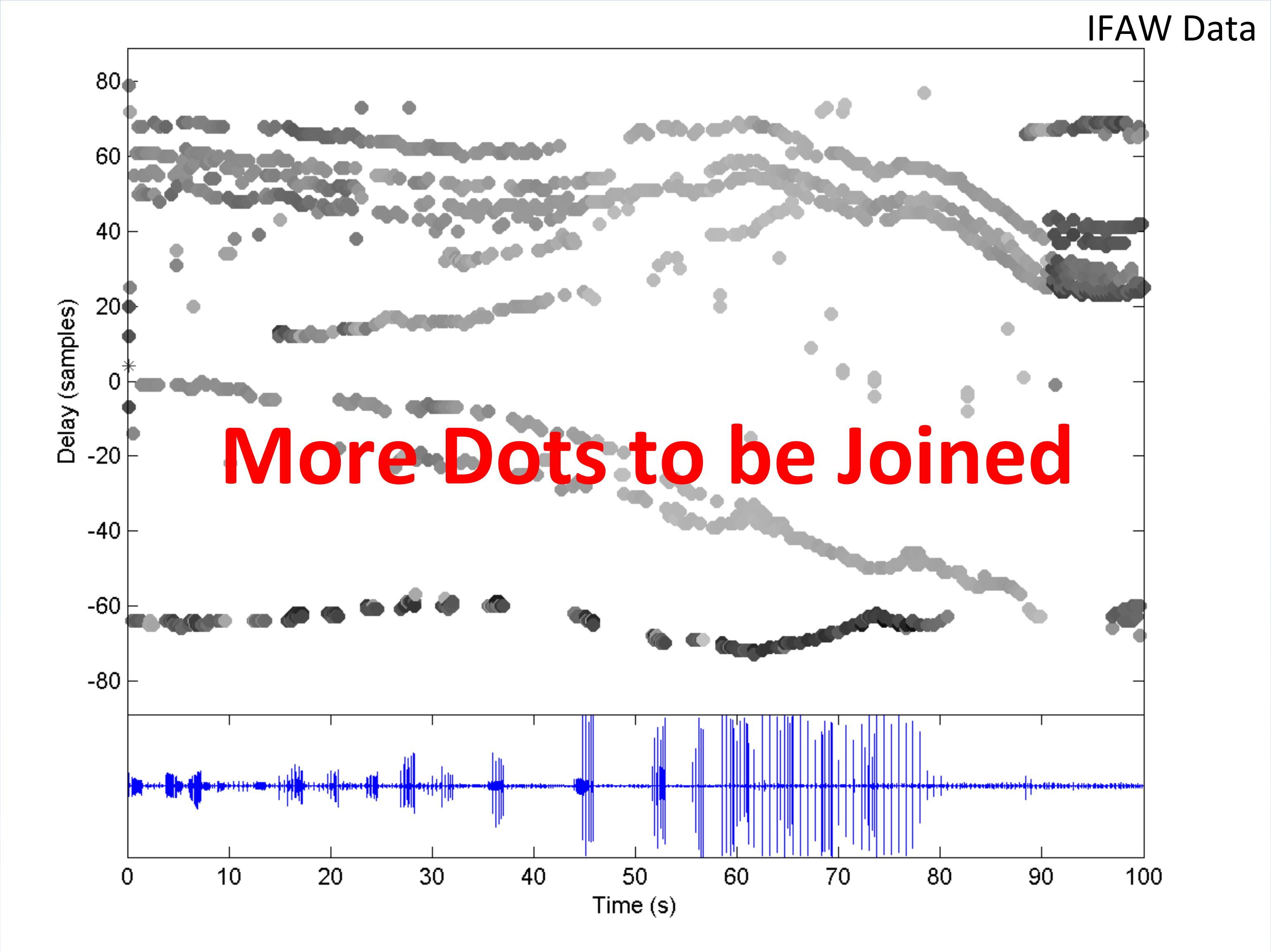
- Localising sperm whales using towed hydrophone arrays.


Processing Chain



Example Dataset



State Space Modelling

- A tracker relies on an underlying model of how parameters change with time.
- The states ($\underline{x}_n$) are the things that characterise what we are looking at
  - They may, or may not, be directly measureable.
- A state space model takes the form of 2 equations

State Update $\boxed{\underline{x}_n = A\underline{x}_{n-1} + C\underline{u}_n}$ Describes how the states change with time

Measurement $\boxed{\underline{y}_n = B\underline{x}_n + D\underline{v}_n}$ Describes how what we measure ($\underline{y}_n$) relates to the states.

A State Space Model for Dolphin Whistles

- State representation

Current whistle frequency

$$\underline{x}_n = \begin{bmatrix} f(n) \\ r(n) \end{bmatrix}$$

Current whistle chirp rate

- State transition

Time between segments

$$f(n) = f(n-1) + Tr(n-1)$$

$$r(n) = r(n-1) + u(n)$$

$$\underline{x}_n = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \underline{x}_{n-1} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(n)$$

Plant noise

- Measurement

$$\boxed{y_n} = \begin{bmatrix} 1 & 0 \end{bmatrix} \underline{x}_n + v(n)$$

Measurement noise

I am assuming we are measuring only frequency.
It is possible to estimate sweep rate accurately and efficiently too.

Kalman $\boxed{\text{Filter}}$

It's a filter Jim,
but not as we know it!

- The Kalman filter allows one to estimate the state sequence ($\underline{x}_n$) from the sequence of measured data ($\underline{y}_n$).
- It is optimal assuming:
  1) The processes $\underline{u}_n$ and $\underline{v}_n$ are Gaussian (normal).
  2) The transitions and measurements are linear, A and B are independent of $\underline{x}_n$ and $\underline{y}_n$ (they do not have to be constant).
  3) The model is accurate!!

Kalman Update Equations

- The equations for the Kalman filter can be written as:

$$\underline{\hat{x}}_n = A\underline{x}_{n-1}$$

Update state estimate

$$\hat{P}_n = AP_{n-1}A^T + CR_{uu}C^T$$

$$K = \hat{P}_n B^T \left(B\hat{P}_n B^T + DR_{vv}D^T \right)^{-1}$$

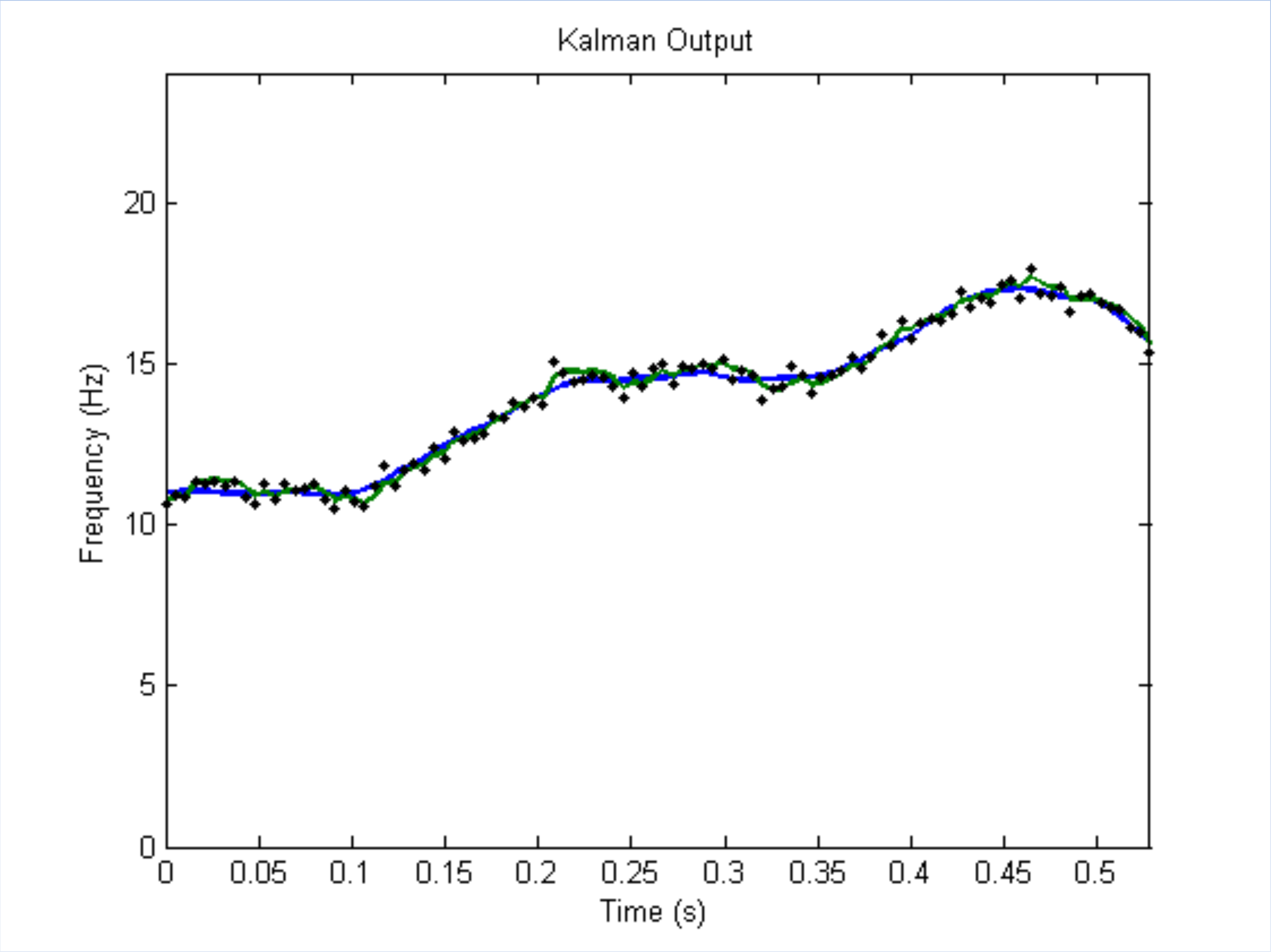
$$\underline{x}_n = \underline{\hat{x}}_n + K\underline{\left(y(n) - B\underline{\hat{x}}_n \right)}$$

Refine estimate

$$P_n = \hat{P}_n - BK\hat{P}_n$$

Error between actual measurement and predicted measurement.

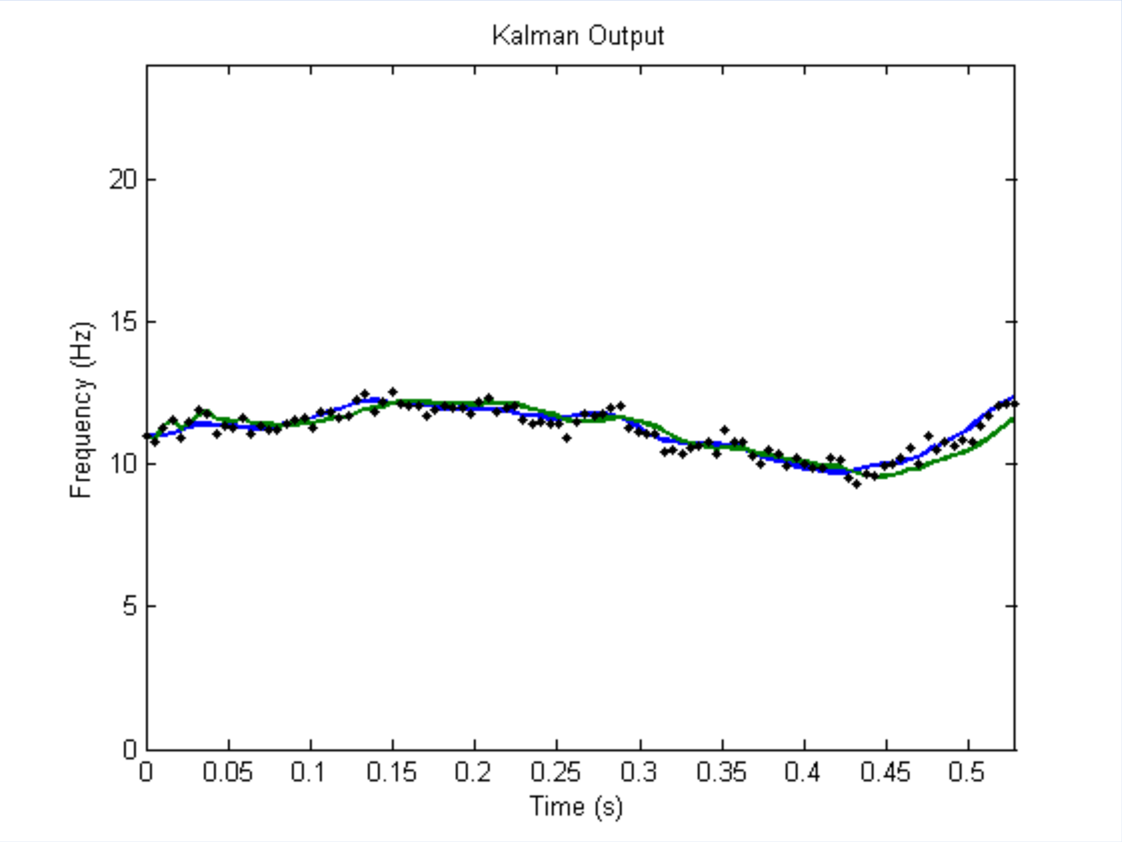
Example



Kalman Output
Frequency (Hz)
Time (s)
0
5
10
15
20
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5

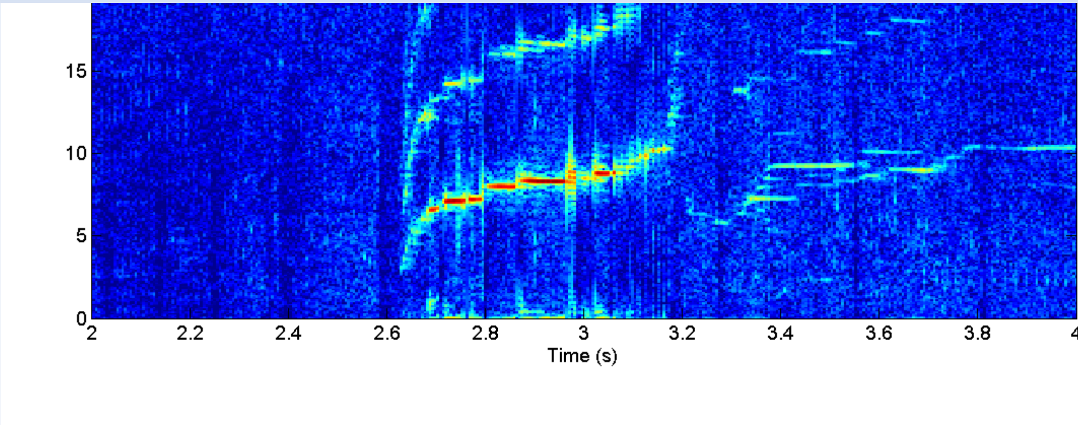
Effect of Model Mismatch

Using a Kalman filter with incorrect model parameters does not, in general, stop it working, it just removes the claim of optimality.



Limitations of Kalman Filters

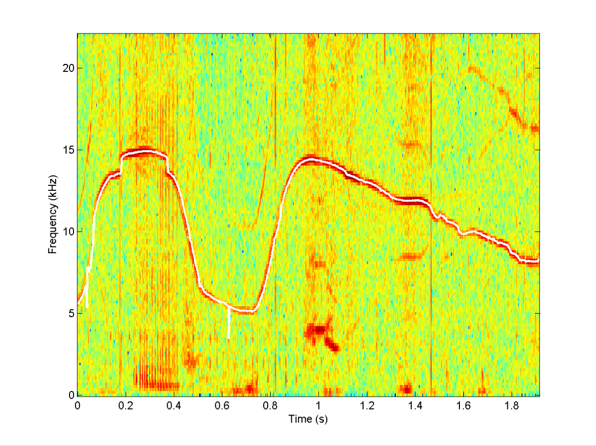
- Kalman filters can run into problems when:
  - State update equations are non-linear
    - Example: Sperm whales have an effective maximum swim speed, there are constraints which one might wish to apply - this leads to non-linearity.
  - Noise processes may be non-Gaussian
    - Example: Dolphin whistles commonly contain frequency jumps.
  - Both non-linear and non-Gaussian



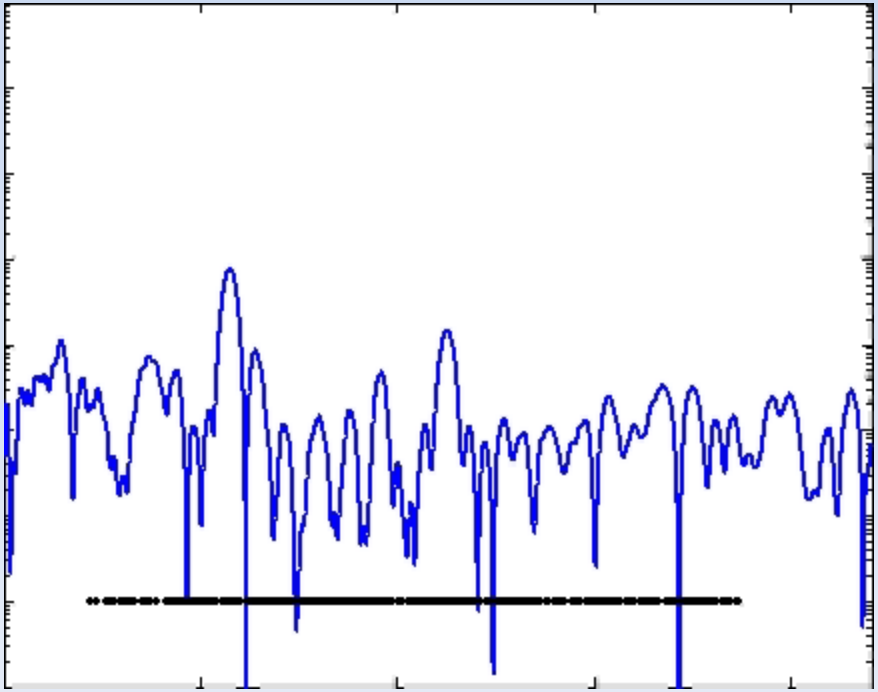
Variants on the Kalman Filter

- The extended Kalman filter (EKF)
  - Copes with non-linearity using local linearisation
- The Unscented Kalman filter (UKF)
  - Approximates probability density functions as Gaussian
- Particle filters
  - Based on point approximations (Monte Carlo methods)

Particle Filters



- Sequential Monte-Carlo method:
  - Very general (non-linear, non-Gaussian problems)
  - Can be computationally demanding



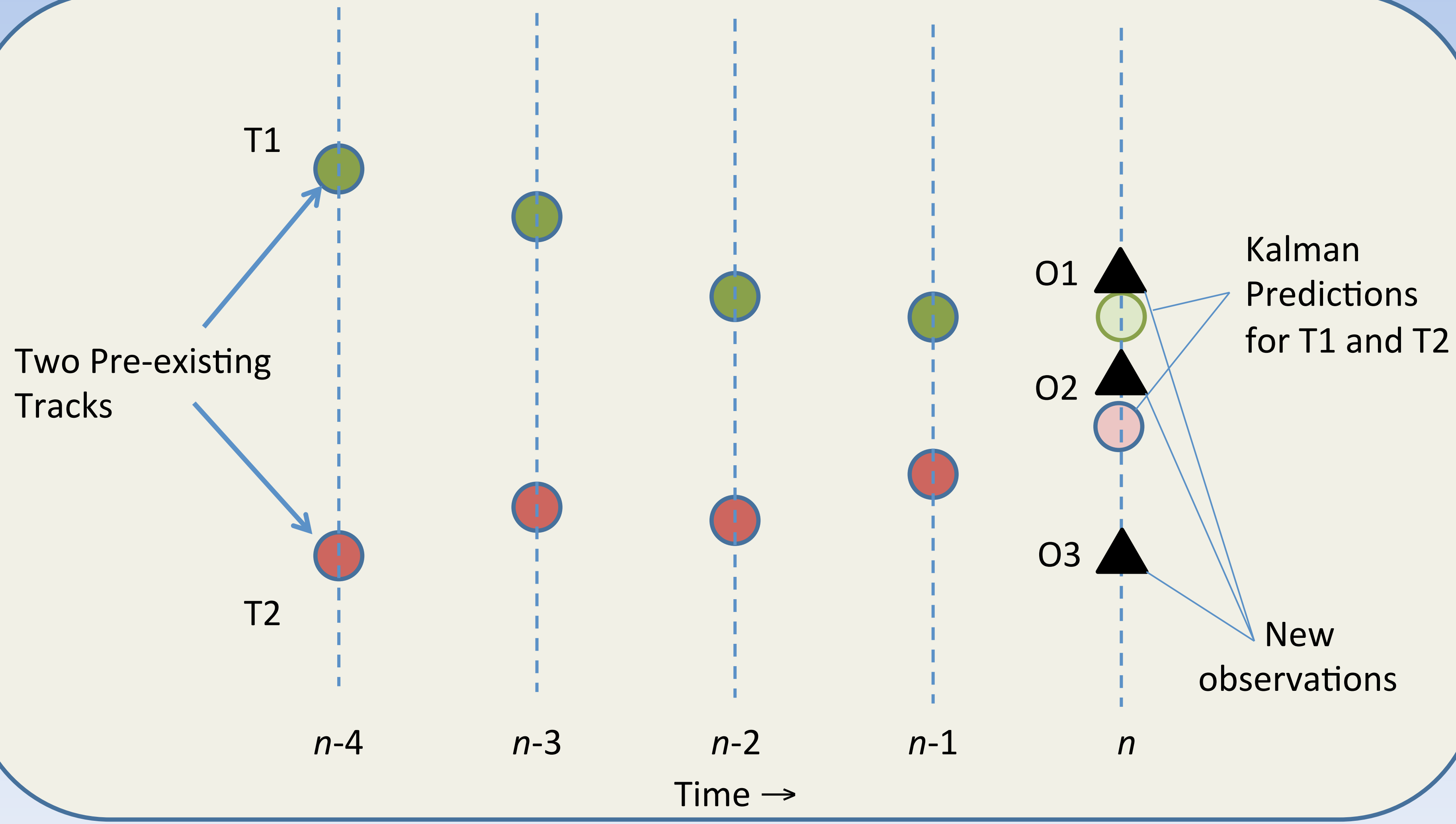
The **Real** Problem

- Kalman filters (and its cousins) are all assume that there is one source – single target tracking.
- Not realistic in most applications.
- Methods that cope with more than one source are called Multi-Target Trackers (MTTs).
  - Note the number of sources is typical unknown and changing through time, animals start and stop vocalising (without informing you!)

Key Components of the Solution

- How do we cope with a time varying, unknown, number of targets/sources/animals?
- Being robust to:
  - Missed detections
  - False alarms
- How do we link a new set of observations to the current list of tracks?

General Framework



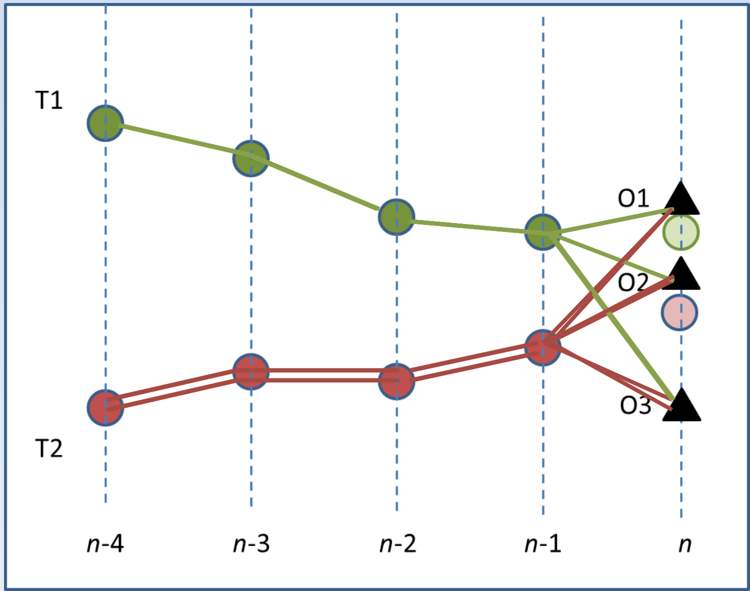
Hypotheses

- There are many ways of combining the new measurements to the existing tracks.
- Leading to a set of hypotheses:
  - H_1: O1 belongs to T1, O2 belongs to T2, O3 is a New Track.
  - H_2: O1→ T1, O3 → T3, O2 is NT.
  - H_3: O2→ T1, O1 → T2, O3 is NT
  - H_4: O2→ T1, O3 → T2, O1 is NT
  - H_5: O3→ T1, O1 → T2, O2 is NT
  - H_6: O3→ T1, O2 → T2, O1 is NT

  But we don't stop there ……
  - H_7: O1→ T1, O2 and O3 are NT
  - H_8: O1→ T2, O2 and O3 are NT
  - H_9: O2→ T1, O1 and O3 are NT
  - H_{10}: O2→ T1, O1 and O3 are NT
  - H_{11}: O2→ T1, O1 and O3 are NT
  - H_{12}: O2→ T1, O1 and O3 are NT

  And finally
  - H_{13}: O1, O2 and O3 are all NT

Note each observation is only allowed to be associated with one track.



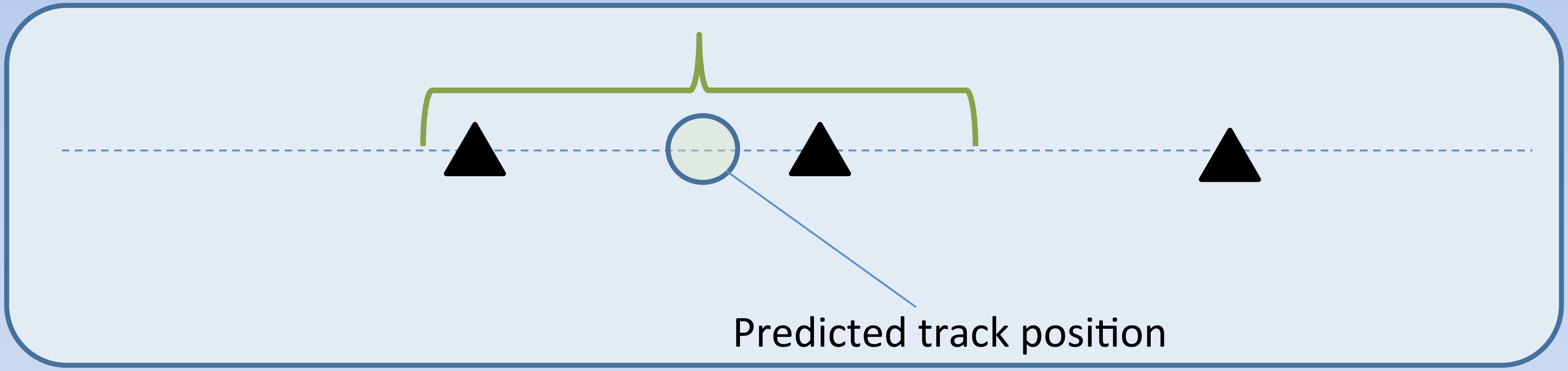
Track Scoring

- We can allocate a cost to each track using log-likelihoods.
- The Kalman filter provides an estimate of the variance about each estimated location and the log-likelihood for a track is updated using:

$$\Delta S = \left(Tm - On\right)^2 / 2\sigma^2$$

- When we include an observation in a track, we increment that track's score using the above.
- Scores are also allocated to starting a new track, false alarms and missed detections.

Range Gating



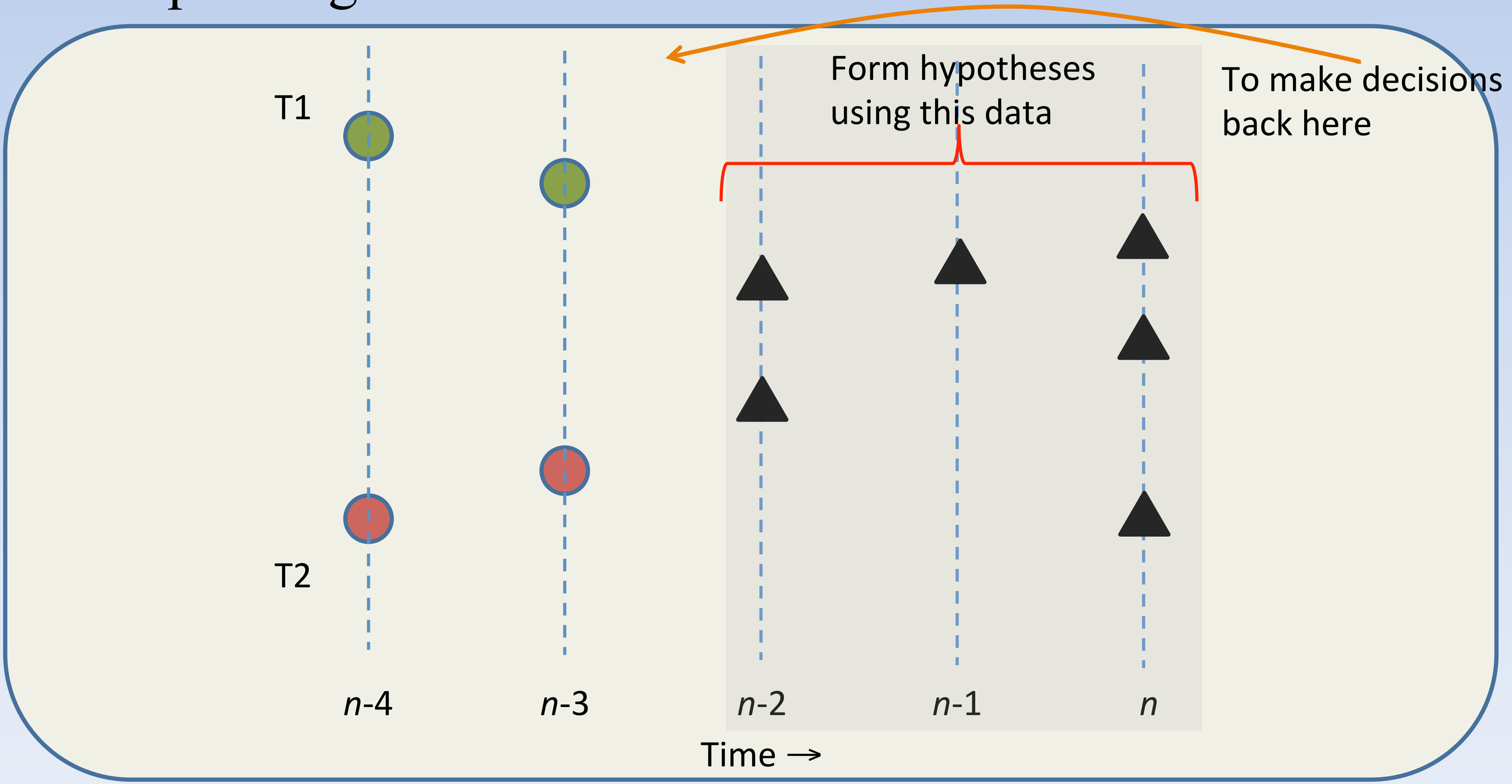
- Using the variances from the Kalman filter we can define a confidence interval (the range gate).
- One can then only form hypotheses which link observations within the gate.
- Greatly reduces the number of hypotheses to consider.

A Single Scan MHT (Not really an MHT yet!)

- If we were to build an (overly) simplified MHT based on single scans then it might look like:
  - Get a new set of observations
  - Enumerate all of the hypotheses
  - Find the cost of each hypothesis
  - Pick the one with the highest score (log-likelihood)
  - Move to the next set of observations
- This method is essentially what is called a global nearest neighbour tracker.

MHT Principle

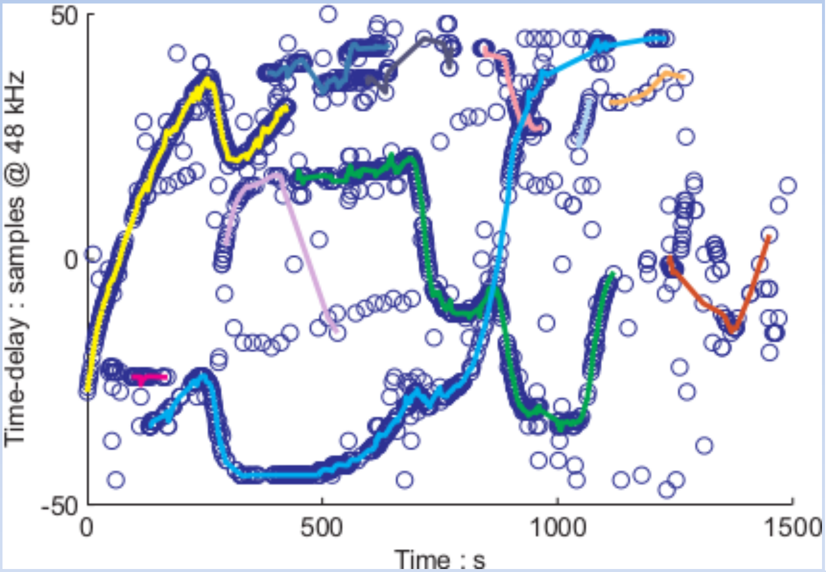
- An MHT defers decisions, it looks at hypotheses spanning several sets of observations.

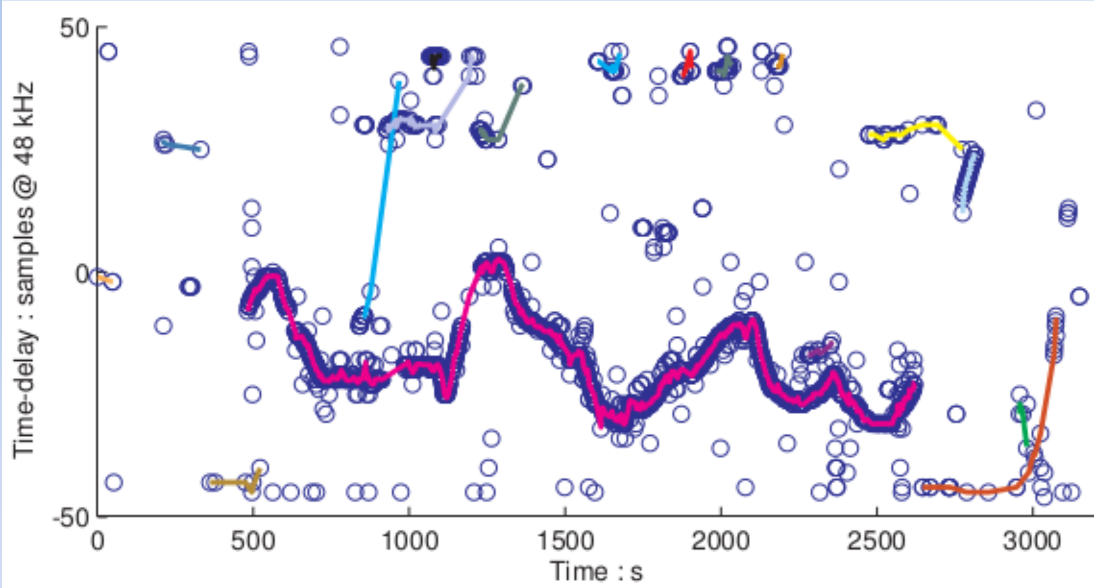


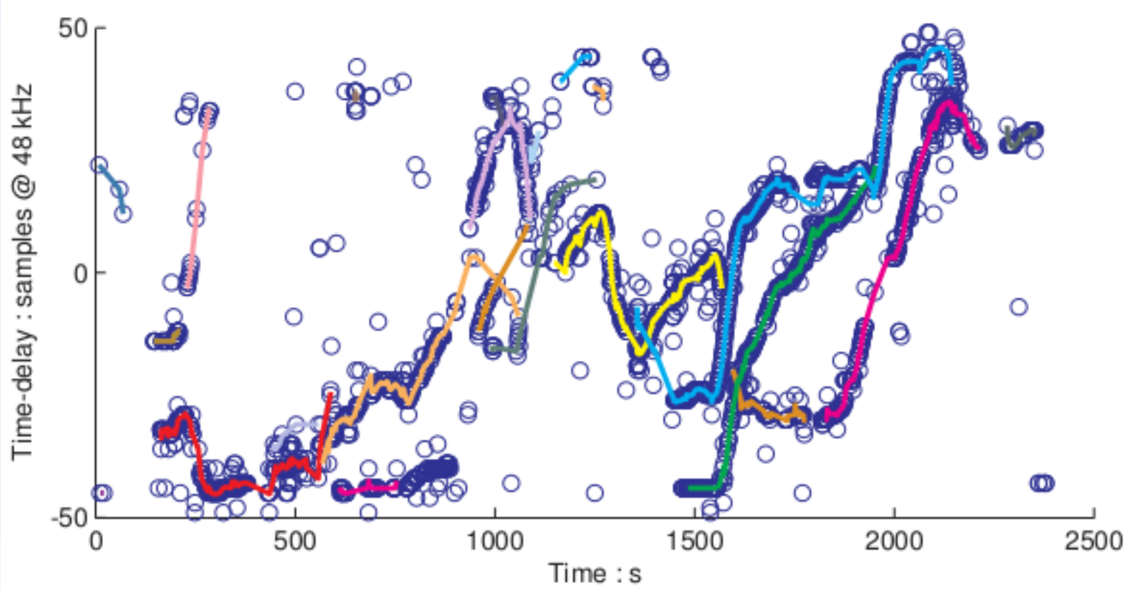
Hypothesis Overload

- Hypotheses are updated recursively
  - The set of hypotheses at time *n* can be generate from those at time *n*-.
- This still leads to a very large number of hypotheses which need to be managed.
  - Using track gates helps
  - The different strategies for organising and maintaining hypotheses lead to different "flavours" of MHT.
  - Commonly a fixed number of hypotheses are brought forward at each step- there exist efficient algorithms for computing the *k* best solutions.

Results: Sperm Whale Tracking (MHT)







Comments on MHTs

- Probably the most widely implemented trackers.
- Largely heuristic, there is theoretical backing for elements, but none for the overall structure.
- Complex implementation.
- Selecting parameters so the tracker functions well is not always trivial.

Model Order

- A tracker needs to cope with signals starting and stopping (to be of any use).
- A theoretical framework in which model order can change not well established.
  - Commonly one uses reversible MCMC algorithms.
    - Particle filters in which particles for different orders co-exist.
- One such framework uses the idea of Finite Set Statistics (FISST).

Trackers Based on FISST

- The solution produced by FISST is generally in tractable and needs to be approximated.
- These trackers don't explicitly solve the track association problem, this needs an additional final step.
- There are various methods for achieving this…
  - Probability Hypothesis Density (PHD) trackers, in various guises:
    - Gaussian Mixtures (GM-PHD)
    - Sequential Monte Carlo (SMC-PHD)
    - Cardinalised PHD (CPHD)
  - Other methods too including the multi-Bernoulli filters

  ….. It's a zoo out there

Gaussian Mixture PHD Algorithm

Algorithm 5.1: GM-PHD Filter

$\left[\left\{w_{k|k}^{(i)}, m_{k|k}^{(i)}, P_{k|k}^{(i)}\right\}_{i=1}^{J_k}\right]$ =GM-PHD$\left[\left\{w_{k-1}^{(i)}, m_{k-1}^{(i)}, P_{k-1}^{(i)}\right\}_{i=1}^{J_{k-1}}, Z_k\right]$

Prediction Stage:

Prediction for Newborn Target:

Set $i = 0$

Predict weights, means and the associated covariances of the Gaussian mixture density according to

for $j = 1, \ldots, J_{\gamma,k}$

$$i := i + 1 \tag{5.31}$$

$$w_{k|k-1}^{(i)} = w_{\gamma,k}^{(j)} \tag{5.32}$$

$$m_{k|k-1}^{(i)} = m_{\gamma,k}^{(j)} \tag{5.33}$$

$$P_{k|k-1}^{(i)} = P_{\gamma,k}^{(j)} \tag{5.34}$$

end

Prediction for Spawning target:

for $j = 1, \ldots, J_{\beta,k}$

for $l = 1,2, \ldots, J_{k-1}$

$$i := i + 1 \tag{5.35}$$

$$w_{k|k-1}^{(i)} = w_{k-1}^{(l)} w_{\beta,k}^{(j)} \tag{5.36}$$

$$m_{k|k-1}^{(i)} = d_{\beta,k-1}^{(j)} + F_{\beta,k-1}^{(j)} m_{k-1}^{(l)} \tag{5.37}$$

$$P_{k|k-1}^{(i)} = Q_{\beta,k-1}^{(j)} + F_{\beta,k-1}^{(j)} P_{k-1}^{(l)} \left(F_{\beta,k-1}^{(j)}\right)^T \tag{5.38}$$

end

end

Prediction for Persistent Target:

for $j = 1, \ldots, J_{k-1}$

$$i := i + 1 \tag{5.39}$$

$$w_{k|k-1}^{(i)} = p_{S,k} w_{k-1}^{(j)} \tag{5.40}$$

$$m_{k|k-1}^{(i)} = F_{k-1} m_{k-1}^{(j)} \tag{5.41}$$

$$P_{k|k-1}^{(i)} = Q_{k-1} + F_{k-1} P_{k-1}^{(j)} (F_{k-1})^T \tag{5.42}$$

end

$$J_{k|k-1} = i \tag{5.43}$$

Update Stage:

Construction of PHD updates components using KF

for $j = 1, \ldots, J_{k|k-1}$

$$\eta_{k|k-1}^{(j)} = H_k m_{k|k-1}^{(j)} \tag{5.44}$$

$$S_{k|k}^{(j)} = R_k + H_k P_{k|k-1}^{(j)} (H_k)^T \tag{5.45}$$

$$K_{k|k}^{(j)} = P_{k|k-1}^{(j)} (H_k)^T \left[S_{k|k}^{(j)}\right]^{-1} \tag{5.46}$$

$$P_{k|k}^{(j)} = \left[\mathbb{I} - K_{k|k}^{(j)} H_k\right] P_{k|k-1}^{(j)} \tag{5.47}$$

end

Update GM components:

for $j = 1, \ldots, J_{k|k-1}$

$$w_k^{(j)} = (1 - p_{D,k}) w_{k|k-1}^{(j)} \tag{5.48}$$

$$m_k^{(j)} = m_{k|k-1}^{(j)} \tag{5.49}$$

$$P_k^{(j)} = P_{k|k-1}^{(j)} \tag{5.50}$$

end

Set $l := 0$

for each $z \in Z_k$

$$l := l + 1 \tag{5.51}$$

for $j = 1, \ldots, J_{k|k-1}$

$$w_k^{(l\,J_{k|k-1}+j)} = p_{D,k} w_{k|k-1}^{(j)}\, \mathcal{N}\left(z; \eta_{k|k-1}^{(j)}, S_{k|k}^{(j)}\right) \tag{5.52}$$

$$m_k^{(l\,J_{k|k-1}+j)} = m_{k|k-1}^{(j)} + K_{k|k}^{(j)}\left(z - \eta_{k|k-1}^{(j)}\right) \tag{5.53}$$

$$m_k^{(l\,J_{k|k-1}+j)} = P_{k|k}^{(j)} \tag{5.54}$$

end

$$w_k^{(l\,J_{k|k-1}+j)} := \frac{w_k^{(l\,J_{k|k-1}+j)}}{\kappa_k(z) + \sum_{i=1}^{J_{k|k-1}} w_k^{(l\,J_{k|k-1}+j)}} \text{ for } j = 1, \ldots, J_{k|k-1} \tag{5.55}$$

end

$$J_k = l\,J_{k|k-1} + J_{k|k-1} \tag{5.56}$$

Algorithm 5.2: Pruning for GM-PHD filter

$\left[\left\{\widetilde{w}_{k|k}^{(i)}, \widetilde{m}_{k|k}^{(i)}, \widetilde{P}_{k|k}^{(i)}\right\}_{i=1}^{J_{max}}\right]$ =PRN$\left[\left\{w_{k|k}^{(i)}, m_{k|k}^{(i)}, P_{k|k}^{(i)}\right\}_{i=1}^{J_k}, T, U, J_{max}\right]$

Given T is truncation threshold, U = Merging Threshold , J_{max} = Maximum allowable number of Gaussian terms

Set $l := 0$ and fund the index i for which $w_{k|k}^{(i)}$ is above the truncation threshold T i.e.

$$I = \left\{i = 1,2, \ldots, J_k | w_{k|k}^{(i)} > T\right\} \tag{5.58}$$

while $I \neq \phi$

$l := l + 1$

Find the index $i \in I$ that maximizes $w_{k|k}^{(i)}$

$$j := \underset{i \in I}{arg\,max}\, w_{k|k}^{(i)} \tag{5.59}$$

Find the set of indices of the means of Gaussian components that are within distance U from the Gaussian components with highest weight

$$L := \left\{i \in I \,|\, \left(m_{k|k}^{(i)} - m_{k|k}^{(j)}\right)^{\mathrm{T}} \left(P_{k|k}^{(i)}\right)^{-1} \left(m_{k|k}^{(i)} - m_{k|k}^{(j)}\right) < U\right\} \tag{5.60}$$

Calculate the weights, means and covariances according to

$$\widetilde{w}_{k|k}^{(l)} = \sum_{i \in L} w_{k|k}^{(i)} \tag{5.61}$$

$$\widetilde{m}_{k|k}^{(l)} = \frac{1}{\widetilde{w}_{k|k}^{(l)}} \sum_{i \in L} w_{k|k}^{(i)} m_{k|k}^{(i)} \tag{5.62}$$

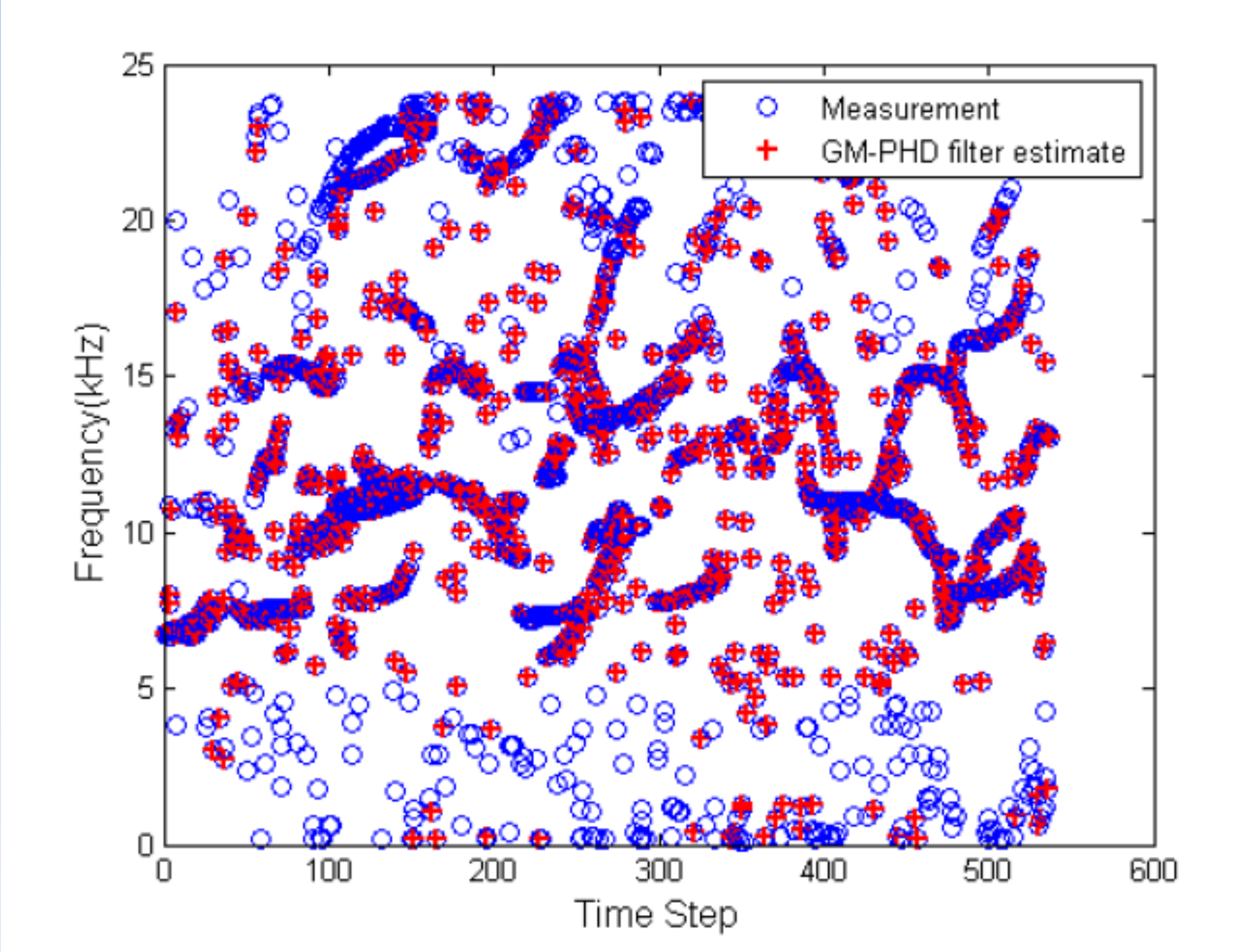
$$\widetilde{P}_{k|k}^{(l)} = \frac{1}{\widetilde{w}_{k|k}^{(l)}} \sum_{i \in L} w_{k|k}^{(i)} \left(P_{k|k}^{(i)} + \left(\widetilde{m}_{k|k}^{(l)} - m_{k|k}^{(i)}\right)\left(\widetilde{m}_{k|k}^{(l)} - m_{k|k}^{(i)}\right)^T\right) \tag{5.63}$$

Set $I := I \backslash L$ (5.64)

end while

If $l > J_{max}$ then replace $\left\{w_{k|k}^{(i)}, m_{k|k}^{(i)}, P_{k|k}^{(i)}\right\}_{i=1}^{l}$ by those of the J_{max} largest weights.

Results: Dolphin Whistle (PHD)



Conclusions

- Tracking has the potential to extend what can be achieved autonomously ….. it is not perfect and definitely not a panacea … but is under utilised.
- MHTs are *ad hoc* (to a large extend) and can take effort to tune to a problem …. but are still useful.
- PHD trackers have considerable promise, they are computationally reasonable (despite the large number of equations it takes to define the algorithm!)

Chirp Rate Estimation: Methods

- There are a range of methods that can be used to estimate the rate of change of frequency of a narrowband signal in noise.
  - Based on the curvature of the peak in the FT
  - The cubic phase transform (CPT)
  - Fractional Fourier Transform (FrFT)
  - Reassignment based method
  - Maximum likelihood

Chirp Rate Estimation: Performance