Track-Before-Detect for Active Sonar

Han Xuan Vu

Thesis submitted for the degree of
Doctor of Philosophy
in
Electrical and Electronic Engineering
at
The University of Adelaide

School of Electrical and Electronic Engineering

THE UNIVERSITY of ADELAIDE

February 3, 2015

Abstract

The detection and tracking of underwater targets with active sonar is a challenging problem because of high acoustic clutter, fluctuating target returns and a relatively low measurement update rate. In this thesis, a Bayesian framework for the detection and tracking of underwater targets using active sonar is formulated. In general, Bayesian tracking algorithms are built on two statistical models: the target dynamics model and the measurement model. The target dynamics model describes the evolution of the target state with time and is almost always assumed to be a Markov process. The typical measurement model approximates the sensor image with a collection of discrete points at each frame and allows point measurement tracking to be performed. This thesis investigates alternative target and measurement models and considers their application to active sonar tracking.

The Markov process commonly used for target modelling assumes that the state evolves without knowledge of its future destination. Random realisations of a Markov process can also display a large amount of variability and do not, in general, resemble realistic target trajectories. An alternative is the reciprocal process, which assumes conditioning on a known destination state. The first key contribution is the derivation and implementation of a Maximum Likelihood Sequence Estimator (MLSE) for a Hidden Reciprocal Process (HRP). The performance of the proposed algorithm is demonstrated in simulated scenarios and shown to give improved state estimation performance over Markov processes for scenarios featuring reciprocal targets.

In point measurement tracking, reducing the sensor data to point detections results in the loss of valuable information. This method is generally sufficient for tracking high Signal-to-Noise Ratio (SNR) targets but can fail in the case of low SNR targets. The alternative to point measurement tracking is to provide the sensor intensity map, an image, as an input into the tracker. This paradigm is referred to as Track-Before-Detect (TkBD). This thesis will focus on a particular TkBD algorithm based on Expectation-Maximisation (EM) data association called the Histogram-Probabilistic Multi-Hypothesis Tracker (H-PMHT) as it handles multiple targets with low complexity. In the second key contribution, we demonstrate a Viterbi implementation of the H-PMHT algorithm, and show that it outperforms the Kalman Filter in the linear non-

Gaussian case.

A problem with H-PMHT is that it fails to model fluctuating target amplitude, which can degrade performance in realistic sensing conditions. The third key contribution addresses this by replacing the multinomial measurement model with a Poisson mixture process. The new Poisson mixture is shown to be consistent with the original H-PMHT modelling assumptions but it now allows for a randomly evolving mean target amplitude state with instantaneous fluctuations. This new TkBD algorithm is referred to as the Poisson H-PMHT. The Bayesian prior on the target state is also modified to ensure more robust performance.

The fourth contribution is a novel TkBD algorithm based on the application of EM data association to a new measurement model that directly describes continuous valued intensity maps and avoids using an intermediate quantisation stage like the H-PMHT. This model is referred to as the Interpolated Poisson measurement model and is integrated into the Probabilistic Multi-Hypothesis Tracker (PMHT) framework to derive a TkBD algorithm for continuous data called the Interpolated Poisson-PMHT (IP-PMHT). The performance of the Poisson H-PMHT and IP-PMHT algorithms are verified through simulations and are shown to outperform the standard H-PMHT in terms of SNR estimation, particularly for scenarios featuring targets with highly fluctuating amplitude.

The final key contribution is the application of several TkBD algorithms based on EM data association to the active sonar problem through a comparative study using trial data from an active towed array sonar. The TkBD algorithms are modified to incorporate changes in target appearance with received array bearing, and are shown to give improved SNR and state estimation performance compared with a conventional point measurement tracking algorithm. The thesis concludes by discussing the limitations of the proposed algorithms and possible avenues for future work.

Publications

- H. X. Vu, S. J. Davey, S. Arulampalam, F. K. Fletcher, and C.C. Lim. A new state prior for the Histogram-PMHT. *IEEE Signal Processing Letters, in preparation*
- H. X. Vu, S. J. Davey, S. Arulampalam, F. K. Fletcher, and C.C. Lim. Histogram-PMHT with an evolving Poisson prior. In *2015 IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, April 2015
- H. X. Vu, S. J. Davey, F. K. Fletcher, S. Arulampalam, R. Ellem, and C.-C. Lim. Track-before-detect for an active towed array sonar. In *Proceedings of Acoustics 2013*, November 2013
- H. X. Vu, S. J. Davey, S. Arulampalam, F. K. Fletcher, and C.-C. Lim. H-PMHT with a Poisson measurement model. In *Proceedings of the 2013 International Conference on Radar (Radar)*, pages 446–451, September 2013
- H. X. Vu and S. J. Davey. Track-before-detect using Histogram PMHT and dynamic programming. In *Proceedings of the 2012 International Conference on Digital Image Computing Techniques and Applications (DICTA)*, pages 1–8, December 2012
- S. J. Davey, H. X. Vu, S. Arulampalam, F. Fletcher, and C.C. Lim. Clutter mapping for Histogram PMHT. In *2014 IEEE Workshop on Statistical Signal Processing (SSP)*, pages 153–156, Gold Coast, Australia, June-July 2014
- S. J. Davey, M. Wieneke, and H. Vu. Histogram-PMHT unfettered. *IEEE Journal of Selected Topics in Signal Processing*, 7(3):435–447, June 2013
- L. B. White and H. X. Vu. Maximum likelihood sequence estimation for hidden reciprocal processes. *IEEE Transactions on Automatic Control*, 58(10):2670–2674, October 2013

Declaration

I, Han Xuan Vu, certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree. I give consent to this copy of my thesis when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968.

The author acknowledges that copyright of published works contained within this thesis resides with the copyright holder(s) of those works.

I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library Search and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

Signature.............................. *Date*............

Acknowledgements

I would like to acknowledge my phenomenal team of supervisors, Sam Davey, Sanjeev Arulampalam, Fiona Fletcher and Cheng-Chew Lim for their ongoing support and encouragement throughout my candidature. I would also like to express my gratitude for their generousity and willingness to share their valuable time and expertise. Their mentorship, guidance and knowledge have been invaluable. Thank you also to Richard Ellem for the provision of trial data used in this research.

I would like to thank my host institutions the School of Electrical and Electronic Engineering at the University of Adelaide and the Maritime Division of the Defence Science and Technology Organisation for their continued support throughout my candidature.

Finally, a sincere thank you to all my friends and family for their unwavering support and patience through the ups and downs of my candidature. A special mention to my partner Chris for taking the brunt of it, without (too much) complaint.

Contents

List of Figures

List of Tables

List of Acronyms

EM Expectation-Maximisation

EKF Extended Kalman Filter

ER Echo-Repeater

GNN Global Nearest Neighbour

HMM Hidden Markov Model

HMC Hidden Markov Chain

HRC Hidden Reciprocal Chain

HRP Hidden Reciprocal Process

H-PMHT Histogram-Probabilistic Multi-Hypothesis Tracker

iid independent and identically distributed

IPDA Integrated Probabilistic Data Association

IP-PMHT Interpolated Poisson - Probabilistic Multi-Hypothesis Tracker

MAP Maximum a Posteriori

MLSE Maximum Likelihood Sequence Estimator

MMSE Minimum Mean Square Error

ML Maximum Likelihood

NN Nearest Neighbour

KF Kalman Filter

pdf probability density function

psf	point spread function
PDA	Probabilistic Data Association
PF	Particle Filter
PMHT	Probabilistic Multi-Hypothesis Tracker
rhs	right hand side
RMS	Root Mean Square
RC	Reciprocal Chain
RP	Reciprocal Process
SMC	Sequential Monte Carlo
SNR	Signal-to-Noise Ratio
TkBD	Track-Before-Detect
UKF	Unscented Kalman Filter

List of Principal Symbols

!	Factorial operator
$[\cdot]^T$	Transpose operator
$[\cdot]'$	Indicates that the variable is dependent on estimates from the previous EM iteration
η	Forgetting factor
λ	Poisson mixing rate
λ_t^m	Poisson mixing rate for component m at time t
$\widetilde{\lambda}$	Quantised Poisson mixing rate
$\widetilde{\lambda}_t$	Quantised Poisson mixing rate at time t
$\widetilde{\lambda}_t^m$	Quantised Poisson mixing rate for component m at time t
$\widetilde{\lambda}_t^{im}$	Quantised Poisson mixing rate for component m in pixel i at time t
$\mathbf{\Lambda}$	Collection of Poisson mixing rate terms for all times and components
$\mathbf{\Lambda}'$	Collection of Poisson mixing rate terms at the previous EM iteration for all time and components
π	Multinomial mixing proportion term
π_t^m	Multinomial mixing proportion term for component m in pixel i at time t
Π	Collection of multinomial mixing proportion terms for all times and components
Π'	Collection of multinomial mixing proportion terms at the previous EM iteration for all times and components
μ_t^{im}	Proportion of power from component m in pixel i at time t
$\mathfrak{z}_t^{im}$	Energy from component m in pixel i at time t
$B_{i,j}^k$	Markov bridge transitions

c^2	Quantisation level
f_t	H-PMHT probability density function at time t
f_t^i	H-PMHT per-pixel probability density at time t
$\mathbb{f}_t$	Poisson H-PMHT intensity function at time t
$\mathbb{f}_t^i$	Poisson H-PMHT per-pixel intensity at time t
F	Linear target transition matrix
F_t	Estimated total power in the image at time t as calculated by the H-PMHT
$F_t^{\mathcal{O}}$	Estimated total power in the observed image pixels at time t as calculated by the H-PMHT
$\mathbb{F}_t$	Estimated total power in the observed image pixels at time t as calculated by the Poisson H-PMHT
$G_0(\cdot)$	Clutter distribution
$h(\cdot)$	Point spread function
$h^i\left(\boldsymbol{x}_t^m\right)$	Probability of a shot due to a target $\boldsymbol{x}_t^m$ falls in pixel i
$h^i(\emptyset)$	Probability of a shot due to clutter falls in pixel i
H	Linear measurement function
i	Measurement pixel index
I	Total number observed pixels
K_t^i	Set of components associated with shots in pixel i at time t
K_t^{ir}	Index of the component associated with the r^{th} shot in pixel i at time t
$\mathbf{K}$	Collection of the assignments of measurements to components for all times and components
$\mathbf{L}$	Collection of the precise locations of the shots inside its pixel for all time and components
$\mathbb{m}_t$	Number of point detections at time t
m	Component index
M	Number of components
$\mathbf{n}_t^i$	Quantised measurements (counts) in pixel i at time t
$\mathbf{n}_t^{im}$	Quantised measurements (counts) from component m in pixel i at time t

$\mathbf{n}_t^{ci}$	Quantised unobserved measurements (counts) in pixel i at time t
$\mathbf{N}$	Collection of quantised observed measurements for all times and components
$\mathbf{N}^c$	Collection of quantised unobserved measurements for all times and components
$\|\|\mathbf{N}_t\|\|$	Total number of shots in the observed image at time t
$\|\|\mathbf{N}_t^c\|\|$	Total number of shots in the unobserved image at time t
$\|\|\mathbf{N}_t^{total}\|\|$	Total number of shots in image (from both observed and unobserved pixels) at time t
$\mathbf{O}$	Observer
Q	Process noise covariance
$Q^{(H)}$	H-PMHT auxiliary function
$Q^{(P)}$	Poisson H-PMHT auxiliary function
$Q^{(IP)}$	IP-PMHT auxiliary function
Q_{ijl}	Reciprocal three point transition function
r	Measurement shot index
R	Measurement covariance matrix
S	Total number of image pixels (unobserved and observed)
t	Time index
T	Number of time scans
$\boldsymbol{x}_t^m$	State of component m at time t
X_t	State in Markov Model
$\mathbf{X}$	Collection of components for all times and components
$\mathbf{X}'$	Collection of components at the previous EM iteration for all times and components
Y_t	Observations in the Markov model at time t
$\boldsymbol{z}_t$	An observed measurement at time t
$\boldsymbol{z}_t^i$	Observed energy in pixel i at time t
$\boldsymbol{z}_t^m$	Observed energy from component m at time t
$\mathbf{Z}$	Collection of observed measurements for all times and components
$\mathbf{Z}_t$	Observed measurements at time t
Z_t	Collection of observed measurements up until time t

$\mathbf{Z}^c$ Collection of unobserved measurements for all times

$\mathbf{Z}_t^c$ Collection of unobserved measurements up to time t

$||\mathbf{Z}_t||$ Total observed energy in image at time t