Extensions to the Probabilistic Multi-Hypothesis Tracker for Tracking, Navigation and SLAM

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# Contents

1 Introduction ................................................. 1
   1.1 Contributions ........................................... 3
   1.2 Thesis Overview ....................................... 3

2 Background .................................................. 7
   2.1 Data Association ....................................... 7
      2.1.1 Nearest Neighbour .................................. 8
      2.1.2 Probabilistic Data Association Filter .......... 8
      2.1.3 Probabilistic Multi-Hypothesis Tracker ..... 9
   2.2 State Estimation ....................................... 10
      2.2.1 Problem Definition ................................ 11
      2.2.2 Target Dynamic Models ........................... 11
      2.2.3 Measurement Model ................................ 14
      2.2.4 Kalman Filter .................................... 15
      2.2.5 Extended Kalman Filter .......................... 16
      2.2.6 Unscented Kalman Filter ......................... 17
      2.2.7 Particle Filter .................................... 19
   2.3 Probabilistic Multi-Hypothesis Tracker ............... 21
      2.3.1 Problem Definition ................................ 21
      2.3.2 PMHT for multi-target tracking ................. 22

3 PMHT with time uncertainty ................................. 27
   3.1 Introduction ............................................ 27
   3.2 Problem Formulation .................................... 28
   3.3 PMHT for tracking with timing uncertainty ........... 29
CONTENTS

3.4 Performance Analysis ..................................................... 34
3.5 Comparison of PMHT-t with other Methods .......................... 41
  3.5.1 PMHT-t Solution ..................................................... 44
  3.5.2 Sliding Window PMHT-t ............................................ 46
  3.5.3 Alternative Algorithms ............................................ 48
  3.5.4 Performance Analysis ............................................. 49
3.6 Conclusion ................................................................. 51

4 PMHT Path Planning .......................................................... 53
  4.1 Introduction ............................................................. 53
    4.1.1 Background ....................................................... 54
    4.1.2 Proposed Approach ............................................... 56
  4.2 Problem Formulation ................................................... 57
  4.3 Path planning problem ................................................ 59
  4.4 PMHT for multiple platform path planning ......................... 61
  4.5 Simulation Results .................................................... 65
  4.6 Tradeoff between smoothness and proximity ....................... 71
  4.7 Locale Density Dependence .......................................... 73
  4.8 Genetic Algorithm Solution to the Travelling Salesmen Problem 77
    4.8.1 GA-TSP with PMHT Smoother ................................. 79
    4.8.2 Path Planning Comparison .................................... 79
  4.9 Sliding batch PMHT Path Planning ................................ 88
  4.10 PMHT-pp for Indoor Environments ................................. 91
    4.10.1 PMHT-pp-pf Indoor Strategies .............................. 91
    4.10.2 PMHT-pp-pf Indoor Results .................................. 92
  4.11 PMHT-pp with Non-Homogeneous Locales .......................... 98
    4.11.1 Non-Homogeneous Locales .................................... 98
    4.11.2 PMHT-pp with Priority as a Continuous Density .......... 99
    4.11.3 Simulation Example ................................ .......... 102
  4.12 Conclusion ............................................................. 105

5 PMHT-c for SLAM ............................................................. 107
  5.1 Introduction ............................................................. 107
5.2 Problem Formulation .................................................. 110
5.3 SLAM formulation .................................................... 111
5.4 The PMHT with Classification in SLAM ......................... 114
5.5 Performance Analysis ................................................ 117
  5.5.1 Simulated results .............................................. 117
  5.5.2 Victoria Park Data ............................................. 123
5.6 Conclusions .......................................................... 127

6 Conclusion ............................................................... 129
  6.1 Tracking with Time Uncertainty ................................. 129
  6.2 Multiple Platform Path Planning ............................... 130
  6.3 SLAM with classifications ....................................... 131
  6.4 Future Work ....................................................... 132

A Source Code Listing .................................................. 133
  A.1 PMHT-t Source Code ............................................. 133
  A.2 PMHT-pp Source Code ........................................... 136
  A.3 PMHT-c SLAM Source Code .................................... 141
# List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>Time error pmf</td>
<td>35</td>
</tr>
<tr>
<td>3.2</td>
<td>PMHT-t Scenario 1 Tracking Results</td>
<td>37</td>
</tr>
<tr>
<td>3.3</td>
<td>PMHT-t Scenario 2 Tracking Results</td>
<td>39</td>
</tr>
<tr>
<td>3.4</td>
<td>PMHT-t Scenario 2 with Clutter Tracking Results</td>
<td>42</td>
</tr>
<tr>
<td>4.1</td>
<td>Locale Example Map</td>
<td>58</td>
</tr>
<tr>
<td>4.2</td>
<td>PMHT-pp assigned trajectories evolution for 4 platforms</td>
<td>67</td>
</tr>
<tr>
<td>4.3</td>
<td>Assorted PMHT-pp Planned Trajectories</td>
<td>68</td>
</tr>
<tr>
<td>4.4</td>
<td>Converged estimates of $\Pi^k$</td>
<td>70</td>
</tr>
<tr>
<td>4.5</td>
<td>Converged estimates of $\Pi^f$</td>
<td>70</td>
</tr>
<tr>
<td>4.6</td>
<td>PMHT-pp Tradeoff using ratio between $Q$ and $R$</td>
<td>72</td>
</tr>
<tr>
<td>4.7</td>
<td>PMHT-pp with varied grid of locales</td>
<td>74</td>
</tr>
<tr>
<td>4.8</td>
<td>PMHT-pp with varied random locales</td>
<td>76</td>
</tr>
<tr>
<td>4.9</td>
<td>GA-TSP with a grid of locales</td>
<td>78</td>
</tr>
<tr>
<td>4.10</td>
<td>Initial priors for PMHT-pp smoothing</td>
<td>80</td>
</tr>
<tr>
<td>4.11</td>
<td>GA-TSP with PMHT-pp smoothed output</td>
<td>81</td>
</tr>
<tr>
<td>4.12</td>
<td>Results for 4 platforms and grid of locales</td>
<td>83</td>
</tr>
<tr>
<td>4.13</td>
<td>Results for 3 platforms and random locales</td>
<td>84</td>
</tr>
<tr>
<td>4.14</td>
<td>Results for 4 platforms and random locales</td>
<td>85</td>
</tr>
<tr>
<td>4.15</td>
<td>Locale distribution between platforms</td>
<td>87</td>
</tr>
<tr>
<td>4.16</td>
<td>Trajectories separated for the four platforms after 8 iterations</td>
<td>89</td>
</tr>
<tr>
<td>4.17</td>
<td>Trajectories at each iteration</td>
<td>90</td>
</tr>
<tr>
<td>4.18</td>
<td>PMHT-pp-pf with grid of locales</td>
<td>94</td>
</tr>
<tr>
<td>4.19</td>
<td>Comparison between PMHT-pp and PMHT-pp-pf</td>
<td>95</td>
</tr>
<tr>
<td>4.20</td>
<td>PMHT-pp-pf with 4 walls</td>
<td>96</td>
</tr>
</tbody>
</table>
LIST OF FIGURES

4.21 PMHT-pp-pf in an indoor environment ........................................... 97
4.22 PMHT-pp with Priority Map Comparison ........................................... 104

5.1 Example platform trajectory with random landmarks. ......................... 119
5.2 Percentage of divergent tracks comparison ......................................... 120
5.3 RMS position estimation error comparison ......................................... 121
5.4 Percentage of divergent tracks with PMHT comparison ......................... 122
5.5 RMS position estimation error with PMHT comparison ........................ 122
5.6 Divergent tracks with different misclassified measurements .................. 123
5.7 Divergent tracks with mismatched misclassified measurements ............... 124
5.8 Histogram of tree widths ................................................................. 125
5.9 PMHT-c estimated trajectory ............................................................. 126
## List of Tables

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>PMHT-t Scenario 1 Monte Carlo RMS results</td>
<td>38</td>
</tr>
<tr>
<td>3.2</td>
<td>PMHT-t Scenario 2 Monte Carlo RMS results</td>
<td>40</td>
</tr>
<tr>
<td>3.3</td>
<td>PMHT-t Scenario 2 with Clutter Monte Carlo RMS results</td>
<td>43</td>
</tr>
<tr>
<td>3.4</td>
<td>Monte Carlo Position RMS Comparison results</td>
<td>50</td>
</tr>
<tr>
<td>3.5</td>
<td>Monte Carlo Timing Error Mean RMS Comparison results</td>
<td>51</td>
</tr>
<tr>
<td>3.6</td>
<td>Monte Carlo Timing Error Precision RMS Comparison results</td>
<td>51</td>
</tr>
<tr>
<td>4.1</td>
<td>PMHT-pp Monte Carlo results for grid of locales</td>
<td>75</td>
</tr>
<tr>
<td>4.2</td>
<td>PMHT-pp Monte Carlo results for random locales</td>
<td>75</td>
</tr>
<tr>
<td>4.3</td>
<td>Path Planning Monte Carlo Comparison results</td>
<td>86</td>
</tr>
</tbody>
</table>
Abstract

Multi-target tracking is a problem that involves estimating target states from noisy data whilst simultaneously deciding which measurement was produced by each target. The Probabilistic Multi-Hypothesis Tracker (PMHT) is an algorithm that solves the multi-target tracking problem. This thesis presents extensions to the PMHT to address problems that may arise in the use of real sensors and considers multi-target tracking techniques for use in other applications such as autonomous vehicles.

It is generally assumed that a sensor collects a set of noisy position measurements at known times. In some situations, the time information may not be reliable and cause filtering issues. This thesis derives an extension to the PMHT that introduces an assignment index that identifies the true time at which a measurement was collected. This extension of the PMHT allows for tracking on measurements with time errors, such as time delays. A further extension allows the PMHT algorithm to simultaneously estimate the time error parameters whilst tracking targets.

The above extension is applied to the problem of planning paths for multiple platforms to explore an unknown area. Given a set of locales to be visited and the platform initial positions, the path planning problem has the same mathematical form as a multi-target tracking problem, with locales as measurements and the platforms as targets. The extended PMHT algorithm uses hypothesised time-stamps to associate locales to platforms and times simultaneously.

Autonomous vehicles are expected to use information from their sensors to navigate and map their environment. Simultaneous localisation and mapping (SLAM) is the name given to this task and is essentially a multi-target tracking problem. This thesis proposes the use of PMHT and landmark classification information received with measurements to improve the performance of SLAM.
Declaration

I, Brian Cheung certify that this work contains no material which has been accepted for the award of any other degree or diploma 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.

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Signature

Date
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The Intelligence, Surveillance and Reconnaissance Division of DSTO for allowing me the opportunity to undertake these studies and the computing resources to undergo the work. The School of Electrical and Electronic Engineering at the University of Adelaide for their hospitality and learning environment.

To my wife, Lang for her love, support and understanding throughout my studies. For keeping me well nourished, encouraged when down and for listening to my presentations even when they made no sense to her, I thank you!
## Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU</td>
<td>Central Processing Unit</td>
</tr>
<tr>
<td>DSTO</td>
<td>Defence Science and Technology Organisation</td>
</tr>
<tr>
<td>EIF</td>
<td>Extended Information Filter</td>
</tr>
<tr>
<td>EKF</td>
<td>Extended Kalman Filter</td>
</tr>
<tr>
<td>EM</td>
<td>Expectation Maximisation</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
</tr>
<tr>
<td>GA-TSP</td>
<td>Genetic Algorithm for Travelling Salesmen Problem</td>
</tr>
<tr>
<td>ISRD</td>
<td>Intelligence, Surveillance and Reconnaissance Division</td>
</tr>
<tr>
<td>JPDA</td>
<td>Joint Probabilistic Data Association</td>
</tr>
<tr>
<td>KF</td>
<td>Kalman Filtering</td>
</tr>
<tr>
<td>LNN</td>
<td>Local Nearest Neighbour</td>
</tr>
<tr>
<td>NN-JPDA</td>
<td>Nearest Neighbour - Joint Probabilistic Data Association</td>
</tr>
<tr>
<td>pdf</td>
<td>probability density function</td>
</tr>
<tr>
<td>PF</td>
<td>Particle Filtering</td>
</tr>
<tr>
<td>PHD</td>
<td>Probability Hypothesis Density</td>
</tr>
</tbody>
</table>
pmf probability mass function
PDA Probabilistic Data Association
PMHT Probabilistic Multi-Hypothesis Tracker
PMHT-c Probabilistic Multi-Hypothesis Tracker with Classification measurements
PMHT-t Probabilistic Multi-Hypothesis Tracker with Time measurements
PMHT-pp Probabilistic Multi-Hypothesis Tracker with Path Planning
PMHT-pp-pf Probabilistic Multi-Hypothesis Tracker Path Planner with Particle Filtering
POMDP Partially Observable Markov Decision Processes
RMS Root Mean Square
SLAM Simultaneous Localisation and Mapping
TSP Travelling Salesman Problem
UKF Unscented Kalman Filter
## Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>${\cdot}^T$</td>
<td>Matrix transpose operator.</td>
</tr>
<tr>
<td>$C$</td>
<td>The confusion matrix, gives the probability of observing a particular class given the true class.</td>
</tr>
<tr>
<td>$c_{ij}$</td>
<td>An element of the confusion matrix, $C = {c_{ij}}$.</td>
</tr>
<tr>
<td>$F$</td>
<td>State transition matrix.</td>
</tr>
<tr>
<td>$F_t$</td>
<td>State transition matrix at scan $t$.</td>
</tr>
<tr>
<td>$g_t$</td>
<td>Measurement noise at time $t$.</td>
</tr>
<tr>
<td>$H_t$</td>
<td>Measurement matrix at scan $t$.</td>
</tr>
<tr>
<td>$h_t$</td>
<td>Nonlinear measurement matrix at scan $t$.</td>
</tr>
<tr>
<td>$K$</td>
<td>The set of all assignment indices over the data batch.</td>
</tr>
<tr>
<td>$k_n$</td>
<td>The assignment index for the $n$th measurement. Indicates which model is the true source for that measurement.</td>
</tr>
<tr>
<td>$k_{nt}$</td>
<td>The assignment index for the $n$th measurement at scan $t$. Indicates which model is the true source for that measurement.</td>
</tr>
<tr>
<td>$k_{ntp}$</td>
<td>The assignment index for the $n$th measurement at scan $t$ from sensor $p$. Indicates which landmark is the true source for that measurement.</td>
</tr>
<tr>
<td>$M$</td>
<td>Total number of targets.</td>
</tr>
</tbody>
</table>
m A target index, indicating target $m$.
N Total number of measurements.
$N_s$ Total number of sample or particle points.
$N_t$ Total number of measurements at scan $t$.
$N_{tp}$ Total number of measurements from sensor $p$ at scan $t$.
n A measurement index, indicating measurement $n$.
P Total number of platforms.
$P_d$ The probability that a target is detected.
$P_{t|t}$ The covariance of the state estimate at scan $t$.
$P_{t|t-1}$ The covariance of the predicted state at scan $t$.
$P_0$ The covariance of the assumed distribution of the initial target state for the linear Gaussian case.
p A platform index, indicating platform $p$ in SLAM.
$Q\left(\cdot | (i)\right)$ The EM auxiliary function that is maximised to obtain the iterative parameter estimates. It is a function of the true parameters and their estimates from the previous EM iteration.
$Q$ The process noise covariance
$Q_C$ The part of the auxiliary function dependent on the confusion matrix. This is maximised to find the confusion matrix estimate.
$Q_t$ The process noise covariance at scan $t$.
$Q_X$ The part of the auxiliary function dependent on the target states, $X$.
$Q_{XY}$ The part of the auxiliary function that couples the landmark and sensor states.
$Q_\Pi$ The part of the auxiliary function dependent on the assignment prior, $\Pi$. 

\( Q_k^\Pi \) The part of the auxiliary function dependent on the positional assignment prior, \( \Pi^k \).

\( Q_\tau^\Pi \) The part of the auxiliary function dependent on the time stamp assignment prior, \( \Pi^\tau \).

\( Q_\tau \) The part of the auxiliary function dependent on the time stamp, \( \tau \).

\( q_x \) The unit time variance of noise in x units.

\( q_y \) The unit time variance of noise in y units.

\( R_t \) The measurement covariance matrix at scan \( t \).

\( \hat{R}_t^m \) The synthetic sensor measurement covariance matrix for model \( m \) at scan \( t \).

\( r \) A measurement index for measurements at a particular scan.

\( S_t \) The innovation covariance matrix at scan \( t \). Represents the expected measurement scatter given the current state estimate and its covariance.

\( T \) Total number of scans in the batch.

\( t \) A time index, indicating scan number \( t \).

\( u_t \) Process noise at time \( t \).

\( v \) Probability of a correct measurement time being available.

\( v_t \) Measurement innovation at scan \( t \).

\( W_t \) The Kalman Gain at scan \( t \).

\( w_t \) Measurement noise at time \( t \).

\( w_i^t \) The weight that a particular sample point \( i \) represents the state at time \( t \).

\( w_{tm} \) An assignment weight functions. The posterior probability function of a particular assignment to target \( m \) at scan \( t \) given the current estimated parameters.
*w_{ntm}* \quad \text{An assignment weight. The posterior probability of a particular assignment between measurement } n \text{ to target } m \text{ at scan } t \text{ given the current estimated parameters.}

\(X\) \quad \text{A set of all of the states of all models over the entire batch.}

\(X^m\) \quad \text{A set of all of the states of model } m \text{ over the entire batch.}

\(x_t\) \quad \text{The state at scan } t.

\(x_t^m\) \quad \text{The state of model } m \text{ at scan } t.

\(x_t^i\) \quad \text{Particle } i \text{ to represent the state at scan } t.

\(\hat{x}_{t|t-1}\) \quad \text{The predicted state at scan } t.

\(\hat{x}_t^m\) \quad \text{The state estimate for model } m \text{ at scan } t.

\(Y^p\) \quad \text{A set of all of the states of platform } p \text{ over all scans.}

\(y_t^p\) \quad \text{The state of platform } p \text{ at scan } t.

\(Z\) \quad \text{A set of all of the measurements for the entire batch.}

\(Z^{(x)}\) \quad \text{A set of all of the positional measurements for the entire batch.}

\(Z^{(k)}\) \quad \text{A set of all of the classification measurements for the entire batch.}

\(Z\) \quad \text{A set of all of the measurements for the entire batch.}

\(z_n\) \quad \text{The } n^{th} \text{ measurement.}

\(z_t\) \quad \text{The measurement at scan } t.

\(z_{ntp}^x\) \quad \text{The } n^{th} \text{ positional measurement at scan } t \text{ produced by sensor } p.

\(z_{ntp}^k\) \quad \text{The } n^{th} \text{ classification measurement at scan } t \text{ produced by sensor } p.

\(z_n\) \quad \text{The } n^{th} \text{ measurement received by the sensor or the } n^{th} \text{ locale in the set of locales.}
$z_{nt}$  The $n$th measurement at scan $t$.

$z_n^x$  The position of measurement $n$.

$z_n^\tau$  The time stamp of measurement $n$.

$z_t^m$  The synthetic measurement for target $m$ at scan $t$.

$\hat{z}_t$  The predicted measurement at scan $t$.

$\chi^i_t$  Sample point $i$ to represent the state at time $t$.

$\Delta$  Pixel size of a uniform grid of locales.

$\Delta t$  Time difference between measurement updates.

$\eta_n$  Priority of locale $n$.

$\lambda$  Unknown parameter to estimate the inverse variance of the time stamp error.

$\mu$  Unknown parameter to estimate the mean time stamp error.

$\phi^p_0(y^p_0)$  The prior probability density function for the state of sensor $p$.

$\phi^p_t(y^p_t|y^p_{t-1})$  The evolution probability density function for sensor $p$ at scan $t$.

$\Pi$  The set of all assignment priors for the batch.

$\Pi^k$  The set of all positional assignment priors for the batch.

$\Pi^\tau$  The set of all time stamp assignment priors for the batch.

$\pi^m_t$  The assignment prior for model $m$ at scan $t$.

$\pi^k_{nm}$  The assignment prior for measurement $n$ to model $m$.

$\pi^\tau_{nt}$  The assignment prior for measurement $n$ at scan $t$.

$\psi_0(x_0)$  The prior probability density function for the state.

$\psi^m_0(x^m_0)$  The prior probability density function for the state of model $m$. 
The evolution probability density function for the target at scan $t$.

The evolution probability density function for model $m$ at scan $t$.

Intensity of locales.

The set of all time assignment indices over the data batch.

The true collection time of measurement $n$.

Associated class of each landmark measurement.

The measurement probability density at scan $t$.

The measurement probability density for model $m$ at scan $t$. 
Publications


xxiii