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

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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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Abbreviations

CPU	Central Processing Unit
DSTO	Defence Science and Technology Organisation
EIF	Extended Information Filter
EKF	Extended Kalman Filter
EM	Expectation Maximisation
GA	Genetic Algorithm
GA-TSP	Genetic Algorithm for Travelling Salesmen Problem
ISRD	Intelligence, Surveillance and Reconnaissance Division
JPDA	Joint Probabilistic Data Association
KF	Kalman Filtering
LNN	Local Nearest Neighbour
NN-JPDA	Nearest Neighbour - Joint Probabilistic Data Association
pdf	probability density function
PF	Particle Filtering
PHD	Probability Hypothesis Density

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

$\{\cdot\}^{\mathsf{T}}$	Matrix transpose operator.
C	The confusion matrix, gives the probability of observing a particular class given the true class.
c_{ij}	An element of the confusion matrix, $\mathsf{C} = \{c_{ij}\}$.
F	State transition matrix.
F_t	State transition matrix at scan t.
g_t	Measurement noise at time t.
H_t	Measurement matrix at scan t.
h_t	Nonlinear measurement matrix at scan t.
K	The set of all assignment indices over the data batch.
k_n	The assignment index for the nth measurement. Indicates which model is the true source for that measurement.
k_{nt}	The assignment index for the nth measurement at scan t. Indicates which model is the true source for that measurement.
k_{ntp}	The assignment index for the nth measurement at scan t from sensor p. Indicates which landmark is the true source for that measurement.
M	Total number of targets.

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.
$Q\left(\cdot\|\cdot^{(i)}\right)$	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_Π	The part of the auxiliary function dependent on the assignment prior, Π.

Q_{Π}^{k}	The part of the auxiliary function dependent on the positional assignment prior, Π^k.
Q_{Π}^{τ}	The part of the auxiliary function dependent on the time stamp assignment prior, Π^τ.
Q_τ	The part of the auxiliary function dependent on the time stamp, τ.
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_t^i	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}	An assignment weight. The posterior probability of a particular assignment between measurement n to target m at scan t given the current estimated parameters.
X	A set of all of the states of all models over the entire batch.
X^m	A set of all of the states of model m over the entire batch.
x_t	The state at scan t.
x_t^m	The state of model m at scan t.
x_t^i	Particle i to represent the state at scan t.
$\hat{x}_{t\|t-1}$	The predicted state at scan t.
$\hat{x}_t^m$	The state estimate for model m at scan t.
Y^p	A set of all of the states of platform p over all scans.
y_t^p	The state of platform p at scan t.
Z	A set of all of the measurements for the entire batch.
$Z^{(x)}$	A set of all of the positional measurements for the entire batch.
$Z^{(k)}$	A set of all of the classification measurements for the entire batch.
Z	A set of all of the measurements for the entire batch.
z_n	The nth measurement.
z_t	The measurement at scan t.
z_{ntp}^x	The nth positional measurement at scan t produced by sensor p.
z_{ntp}^k	The nth classification measurement at scan t produced by sensor p.
z_n	The nth measurement received by the sensor or the nth locale in the set of locales.

z_{nt}	The nth measurement at scan t.
z_n^x	The position of measurement n.
z_n^τ	The time stamp of measurement n.
$\tilde{z}_t^m$	The synthetic measurement for target m at scan t.
$\hat{z}_t$	The predicted measurement at scan t.
χ_t^i	Sample point i to represent the state at time t.
Δ	Pixel size of a uniform grid of locales.
Δt	Time difference between measurement updates.
η_n	Priority of locale n.
λ	Unknown parameter to estimate the inverse variance of the time stamp error.
μ	Unknown parameter to estimate the mean time stamp error.
$\phi_0^p(y_0^p)$	The prior probability density function for the state of sensor p.
$\phi_t^p(y_t^p \| y_{t-1}^p)$	The evolution probability density function for sensor p at scan t.
Π	The set of all assignment priors for the batch.
Π^k	The set of all positional assignment priors for the batch.
Π^τ	The set of all time stamp assignment priors for the batch.
π_t^m	The assignment prior for model m at scan t.
π_{nm}^k	The assignment prior for measurement n to model m.
π_{nt}^τ	The assignment prior for measurement n at scan t.
$\psi_0(x_0)$	The prior probability density function for the state.
$\psi_0^m(x_0^m)$	The prior probability density function for the state of model m.

$\psi_t(x_t \mid x_{t-1})$	The evolution probability density function for the target at scan t.
$\psi_t^m(x_t^m \mid x_{t-1}^m)$	The evolution probability density function for model m at scan t.
ρ	Intensity of locales.
τ	The set of all time assignment indices over the data batch.
τ_n	The true collection time of measurement n.
θ^m	Associated class of each landmark measurement.
$\zeta\left(\boldsymbol{z}_t \mid \boldsymbol{x}_t\right)$	The measurement probability density at scan t.
$\zeta\left(\boldsymbol{z}_{nt} \mid \boldsymbol{x}_t^m\right)$	The measurement probability density for model m at scan t.

Publications

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